Systemic Relevance in Financial Markets and Manufacturing Networks

Dissertation
for the Faculty of Economics, Business Administration and Information Technology of the University of Zurich

to achieve the title of
Doctor of Philosophy
in Banking & Finance

presented by
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approved in April 2012 at the request of
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The Faculty of Economics, Business Administration and Information Technology of the University of Zurich hereby authorizes the printing of this Doctoral Thesis, without thereby giving any opinion on the views contained therein.

Zurich, April 4, 2012

Chairman of the Doctoral Committee: Prof. Dr. Dieter Pfaff

Table of Contents

List of Figures

The value of the liability insurance for Credit Suisse and UBS

To be 'too big to fail'[1] - distorted liability insurance premiums across U.S. banks

[1] I use for 'too big to fail' the acronym TBTF.

Losses from time-structured supply chain disruptions

Bottleneck identification in supply chain networks

List of Tables

The value of the liability insurance for Credit Suisse and UBS

To be ‘too big to fail’ - distorted liability insurance premiums across U.S. banks

Losses from time-structured supply chain disruptions

Bottleneck identification in supply chain networks

Part I

Introduction

Introduction and Summary of Research Results

1 Introduction

The recent financial crisis that started 2007, the earthquake in Japan with the subsequent and ongoing nuclear catastrophe from Fukushima in March 2011 or the current European sovereign debt crisis shed light on the complexity, interconnectivity and vulnerability of financial markets.

The financial crisis had its seeds in the decline of the U.S. subprime market, a relatively small market segment. Due to securitization, the impact was widespread and shortly after also contagious to other asset classes. Governments worldwide had to undertake costly interventions. First, they had to bail out large financial institutions to avoid a complete collapse of the financial system. Second, they passed stimulus packages to mitigate the decline in the real economic activity. The disastrous events in Japan were at the heart of a chain of disturbances in the world's supply networks. For instance, in the car industry, shortages of parts delivered from Japan forced General Motors to halt production at some plants in the U.S. and Spain. Most recently, the debt crisis in Europe illustrates the dangers which emanate from a small country like Greece for the financial system or the global economy. In designing the rescue package for Greece, politicians were very intent that private creditors voluntarily accept a loss of half the value of the bonds not proclaiming a credit event. Such a credit event would trigger the payments of credit default swaps on Greece government bonds and therefore affect issuers of default insurance. Since neither the amount nor the number of participating parties is ultimately clear, authorities feared an unpredictable dispersion of losses and shocks also seen at the collapse of Lehman Brothers.

All these described events have in common that singular or peripheral incidents induce widespread disruptions to the provision of the entire respective system as the financial industry or manufacturing network or even have negative consequences for the whole economy. Researchers and politicians have put the objective to identify and limit these systemic risks on their agendas.

This dissertation contributes to this discussion. More precisely, the four research papers that constitute this doctoral thesis (i) study the underlying risks and consequences of systemically important financial institutions in Switzerland and the United States, (ii) discuss regulatory measures which limit these risks, (iii) propose a model for calculating losses due to production disruptions in manufacturing networks, and (iv) compare different measures for the identification of systemic relevant agents in a supply chain network.

2 Summary of Research Results and Contributions

This dissertation consists of four research papers:

- The value of the liability insurance for Credit Suisse and UBS (with Mario Haefeli).
- To be 'too big to fail' - distorted liability insurance premiums across U.S. banks.
- Losses from time-structured supply chain disruptions (with Kamil Mizgier and Stephan Wagner).
- Bottleneck identification in supply chain networks (with Kamil Mizgier and Stephan Wagner).

Their content and contribution are summarized in the following subsections.

2.1 The value of the liability insurance for Credit Suisse and UBS

The financial industry as a whole and the two big banks Credit Suisse (CS) and UBS in particular play an important role for the Swiss economy. More than 10% of the gross domestic product is created by this sector. Moreover, total assets of the entire sector (the two big banks) correspond to a sextuple (quadruple) GDP which is internationally one of the highest ratios (see Swiss National Bank (2011)) and also reflect the concentration risk which emanates from this industry. During the subprime crisis huge losses of UBS made it necessary for the government to intervene. This intervention was not justified by a contract but by the pivotal role of the bank for the financial industry and ultimately the economy as a whole (Expertenkommission zur Limitierung von volkswirtschaftlichen Risiken durch Grossunternehmen (2010)) and is often called 'implicit guarantee'.[2] Consequently, the survival of a systemic relevant bank is secured by a state guarantee which is not reimbursed by the institution itself. There is a natural interest of a society to determine the value of such a guarantee and discuss ways to limit the inherent risk.

In this paper, we estimate the implicit guarantee value for CS and UBS by calculating liability insurance premiums quarterly in a dynamic setup using data from 2004 through 2009. In our liability insurance approach, debtholders, not the shareholders, are protected in the case of a default and the bank is eliminated, i.e., its license is withdrawn. In other words, we compute the guarantee value as if the guarantee for debtholders had been explicit. The calculation of the guarantee value is based on the theory of valuing debt and deposit insurance by Merton (1974, 1977, 1978). We closely follow Lucas and McDonald (2006, 2009), who adapt this theory for detecting the risk inherent in government-sponsored enterprises. The model detects the current crisis by indicating high guarantee values for both banks, CS and UBS, in the years of 2008 and 2009, compared to the lower premiums in earlier years. For instance, for CS (UBS) we obtain a maximum value of 21.3 (12.7) bn CHF in 2008. This is the premium the bank has to pay for debt insurance for one year. Although these numbers seem to be large, compared to profits, one has to take into account the reduced interest payments to depositors which would

[2] To be accurate: we call the guarantee implicit if there does not exist a contract between bank and guarantor although there are reasons to assume that a guarantee exists.

disburden the banks on the other side. The sensitivity of the results with respect to different model specifications and parameters, e.g., jumps in the asset path or various volatility levels, is analyzed. We conduct a policy analysis with respect to political and regulatory relevant and frequently discussed measures, such as increased capital requirements or an augmented number of audits. Strengthened capital requirements and the increased number of audits reduce the guarantee value substantially. A 2% lower liability to asset ratio induces reductions in the highest guarantee values of roughly 13% (26%) for CS (UBS). With a higher number of audits during the crisis the values for the put price are even diminished by a factor of roughly nine.

2.2 To be 'too big to fail' - distorted liability insurance premiums across U.S. banks

The second article of this thesis also considers aspects regarding the implicit guarantee from the government for systemic relevant or 'too big to fail' (TBTF) institutions.[3] Additional to the contingent-claim approach which we already used for the Swiss case (see Subsection 2.1), there exist a second approach for the valuation of the implicit guarantee. The cash-flow or spread based approach estimates the refinancing advantage of a systemic relevant bank in comparison to others. For instance, Baker and McArthur (2009) find in the U.S. a positive spread between the average costs of funds of the two groups indicating that counterparties (debtholders) seem to be able to distinguish TBTF and Non-TBTF institutions or are aware of the existence of implicit guarantees and therefore require a lower risk premium. They state, but do not verify, that if this gap is attributable to the government guarantee it implies a taxpayer subsidy for the TBTF banks.

This paper studies cash-flow as well as contingent-claim approach for financial institutions in the U.S. from 2004 to 2009. First, I investigate differences in refinancing costs of TBTF and Non-TBTF banks using annualized quarterly interest expenses on debt as dependent variable. After controlling for a range of variables which influence the refinancing costs of a firm, I find evidence that TBTF firms could fund their operations under better conditions than their competitors during the last two years, the time the U.S. government implemented an official TBTF policy. In the second part of the paper, I revisit the contingent-claim approach. The estimation is based on balance sheet data as total assets or liabilities and market data as market capitalization and equity volatility. Latter quantities are determined by the market perception about risk and future returns, therefore are also influenced by the implicit state guarantee (see also O'Hara and Shaw (1990), Cordella and Yeyati (2003), Lucas and McDonald (2009) or Peristiani, Morgan, and Savino (2010)). I examine more closely differences in asset volatility between Non-TBTF and TBTF banks and study the impact of the described endogeneity effect on the level of liability insurance premiums across banks. I can show that premiums relative to total assets differ substantially between systemic relevant and other banks during the crisis. In the period from the first quarter 2004 through the fourth quarter of 2007, the difference in relative

[3] I use these expressions interchangeably, but are aware of the fact that systemic relevance can not only be caused by size but also by interconnectivity.

premiums between Non-TBTF and TBTF institutions is 0.23% on average, then it increases to 3.39%. If the gap is attributable to the TBTF policy of the U.S. government, one can argue that the policy was successful in the sense that the guarantee value was relatively lower for TBTF institutions than for the rest of the studied financial sector. The spread corresponds to an absolute value of about $19.25 bn per year taking into account the amount of total assets from TBTF financial firms during this time. Third, the average absolute liability insurance premiums accumulated for TBTF institutions equals approx. $128 bn per year. The analysis of higher capital requirements (target liability-to-asset ratio of 70% as in Admati, DeMarzo, Hellwig, and Pfleiderer (2011)) shows that the average amount can be reduced by around 40%, i.e., potential bailouts should be much cheaper for tax payers.

2.3 Losses from time-structured supply chain disruptions

The last two papers of the dissertation deal with production disruptions in manufacturing networks. In contrast to the work on financial markets where banks are assumed to be already identified as systemic relevant, in this part we are concerned with the loss dispersion in a supply chain network (third paper) and the identification of systemic relevance in the production context (fourth paper).

As a result of fiercer competition, growing customer needs, accelerated globalization of markets and rapidly developing technology, almost all industries have experienced massive pressure to make intrafirm and interfirm business processes more efficient and/or more responsive. Firms outsource manufacturing, research and development activities, source in low-cost countries, reduce inventories and slack, streamline the supply base and collaborate more intensively with other members of the supply chain. Naturally, the potential cost reductions and improved operational efficiencies achieved through these management decisions come at a cost: supply chain networks (SCNs) are becoming large and densely interconnected, which increases the production-inherent complexity and uncertainty. Therefore, predictions regarding output losses from production breakdowns in the supply chain are difficult to make due to the insufficient knowledge of potential hazard events, the interaction of firms and the dispersion of losses through the network.

A model for calculating the loss distribution of an appointed firm (in the following 'focal') due to time-structured disruptions in a given production network is proposed. For each firm in the network, we allow a variety of hazard events which can be idiosyncratic (e.g., machine malfunction) or systematic and affecting more than one firm (e.g., natural catastrophes). We describe the interaction of different hazard events on the firm level and account for the required time for resolving the disruption using renewal-reward processes. The interaction and dispersion of disruption losses across firms are obtained by incorporating the network topology explicitly. The latter modeling aspect allows us to reproduce contagious effects; i.e., idiosyncratic disruptions may affect other firms in the SCN by propagating through existing linkages among firms. By incorporating systematic hazard events and the network topology (contagion), we cover two fundamental aspects of interdependency among firms in SCNs that are essential for estimating the loss distribution from disruptions in each node in the network. We discuss the impact of some basic diversification strategies on one stage (vertical) and across two stages (horizontal). Vertical diversification can be very successful to reduce uncertainty. However, if we anticipate also the effects of other stages the situation changes. Simultaneous production breakdowns on different stages potentially prevent loss propagation and therefore horizontal diversification can be disadvantageous. Clear statements in favor of diversification are more difficult than one could expect. With the help of an implemented stylized example, we quantify the effects of different model specifications or varying risk factors on expected losses and other risk measures. The reconfiguration of the supplier base on the first stage can lead to substantial improvement of the focal firm's risk profile. In collaboration with a big insurance company, we specify the data requirements which are necessary to calculate the losses with the proposed model.

2.4 Bottleneck identification in supply chain networks

As pointed out, the complexity of these networks makes predictions regarding output losses from production breakdowns in the supply chain difficult. In particular, for focal firms it is essential to identify their high risk suppliers. Supply chain risk managers are then enabled to reconfigure the network structure or improve the resilience by introducing additional inventories to mitigate or prevent contagious effects. In network theory, researchers have been working on ways to condense the informational content of a network for a long time. They examined possibilities to describe networks and identify important nodes in a network (see for instance Freeman (1977), Brandes (2008), Opsahl, Agneessens, and Skvoretz (2010))).

In contrast to the conceptual work before, the aim of this paper is to compare a set of measures for the identification of bottlenecks in SCNs. First, we revisit some established measures from social network theory, e.g., degree centrality or betweenness, and analyze them in the SCN context where these are also used (see Kim, Choi, Yan, and Dooley (2011)). We highlight the importance of the nature of the network connections. In SCNs these connections occur on different interaction levels, including information channels, flow of physical goods or in our case loss dispersion induced by production disruptions. Consequently, the informative value can be very limited. Second, we introduce a new methodology for an efficient and accurate detection of firms in a SCN which potentially generate high losses for a focal firm in case of a disruption. We use a simple version of the previous approach (Subsection 2.3). In a simple example, we determine via Monte Carlo simulation the aggregate loss distribution for the focal firm. The loss contribution of the individual firms and hazard events to total losses for the focal firm provides then a risk-adjusted measure. We compare all these measures and naturally find diverse predictions. Our findings support the necessity of an accurate methodology since the results are ambiguous and can be misleading for firm's supply chain management.

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Part II

Research Papers

The value of the liability insurance for Credit Suisse and UBS

Mario Haefeli, Matthias P. Jüttner

A version of this paper is published in the *Journal of Institutional and Theoretical Economics*[*]

This paper was presented at:

- 8th Swiss Doctoral Workshop in Finance, Gerzensee, Switzerland (June 2010)

Abstract

Using an options-based approach, we compute the value of the state guarantee for the liability side of Credit Suisse and UBS. Insurance premiums for these two system-relevant banks are calculated in a dynamic setup from 2004 through 2009 in quarterly steps for time horizons of one and five years. The model captures the characteristics of the current financial crisis and detects the bailout of UBS. Strengthened capital requirements and an increased number of audits reduce the value of the guarantee substantially.

[*] M. Häfeli and M. P. Jüttner (2012), 'The value of the liability insurance for Credit Suisse and UBS,' Journal of Institutional and Theoretical Economics (JITE), 168 (4), forthcoming.

1 Introduction

Governmental interventions in the financial sector have been observed in many countries during the current financial crisis. The systemic relevance of large institutions has necessitated the bailout of many banks. It is often argued that rescue packages for banking systems were important in stabilizing the alarmingly deteriorating liquidity in the interbank market and to prevent spillover effects onto the real economy via the credit market. However, this policy has evident drawbacks. More specifically, the state has to intervene in, and therefore to distort, the market economy and to support private enterprises with the tax yield. Interventions which ensure the survival of large banks may even encourage 'too big to fail' (TBTF) institutions to increase their risky positions, because they enjoy a free state guarantee. This market discipline problem makes future crises and interventions more likely. Although the government can protect the real economy from turmoil in the financial sector, the expenses may increase the default risk of the entire state. In Switzerland, the 'too big to fail' discussion changed rapidly to the topic of 'too big to rescue', since the country is very small compared to the size of the banks and the potential rescue packages. The gross domestic product of Switzerland amounted to over 500 bn CHF, compared to a total asset value of both banks of approximately 2400 bn CHF at the end of 2009.

To avoid situations where governmental interventions are necessary, different regulatory measures and institutional reforms are being publically discussed including raising capital requirements, stronger liquidity measures and increasing the number of audits. Moreover, splitting big banks to obtain system-irrelevant-units, firm size restrictions, contingent convertible bonds or setting up a rescue fund to bail out system critical institutions. However, these approaches have undesirable effects. For example, more severe capital requirements are not able to exonerate governments from the role of lender of last resort. It is unclear how to divide large banks or how to identify the maximum size. Even though holders of contingent convertible bonds - in contrast to equity holders - do not benefit from the profit chance of high risks before conversion and their asking for adequate risk premiums may induce discipline in bank's risk-taking, a well-established market for these instruments and profound knowledge of its shortcomings are not yet existent. For instance, financial stability of the entire banking system may deteriorate if banks hold their contingent convertible bonds mutually to a large extent. Additionally, if debt is converted into equity, this signal may cause investors' panic and exacerbate share price declines. Hence, the gained solvency is lost rapidly and the problem of governmental aid persists. Another solution is to make the implicit state guarantees for large banks explicit, i.e., to impose a premium for deposit insurance by the government. In this case, a 'too big to fail' bank has to pay for the state guarantee accordingly to the size of its liabilities and its risk exposures. Consequently, banks know that they will not be rescued in threatening situations, which solves the market discipline issue, and deposits will be similar to safe bonds supported by the government, which reduces contagion effects within the financial system. Hence, to avoid market discipline problems, one assumes that in the case of a default, only the depositors or lenders to the bank are bailed out, not the shareholders who decide upon an institution's risk policy. It is not our intention to propagate the idea of deposit insurance since it also induces new problems. For example, if deposits become safe bonds, the business activity of the bank changes drastically. Moreover, governments have to expect moral hazard when banks have paid their premiums (see, e.g., Demirgüç-Kunt and Huizinga (2004)). However, to discuss the practicability of deposit insurance and indicate an adequate premium, it is essential to know the approximate magnitudes of the pure guarantee value without considering any externalities.

In this study, we focus on the Swiss situation and compute the guarantee value for Credit Suisse (CS) and UBS quarterly in a dynamic setup using data from 2004 through 2009, as if the guarantee had been explicit.[1] In our liability insurance approach, debtholders are protected in the case of a default, not the shareholders, and the bank is eliminated, i.e., its license is withdrawn. Thus, considering deposit insurance, the emphasis is not on the various interventions observed in the current crisis to ensure a bank's survival. Its potential and costly resurrection after the default is not captured. The calculation of the guarantee value is based on the theory of valuing debt and deposit insurance by Merton (1974, 1977, 1978). We closely follow Lucas and McDonald (2006, 2009), who adapt this theory for detecting the risk inherent in government-sponsored enterprises (GSEs), namely Fannie Mae and Freddie Mac (F&F). These financial institutions were created by the United States Congress. Nevertheless, the securities carry no explicit government guarantee. Due to the implicit guarantee that the government would not allow such important institutions to fail, the buyers of their securities offer them high prices and lenders grant them advantageous interest rates. This implicit guarantee was tested by the subprime mortgage crisis, which forced the U.S. government to bail out and put into conservatorship Fannie Mae and Freddie Mac in September 2008. Although UBS and CS are privately owned and not founded by the government, the implicit guarantee exists, just because of the size of the banks and importance for the Swiss economy.

We extend the approach of Lucas and McDonald in a variety of ways. Contrary to their work, we not only consider a single point in time, but determine the evolution of the guarantee value. We calculate the guarantee value, the value at risk and the expected shortfall quarterly for the time horizon of 2004-2009. Investigating the time before the financial turmoil and incorporating a 'tail event' enables us to examine the entire dynamics of the model predictions throughout the crisis. The model detects the current crisis by indicating high guarantee values for both banks, UBS and CS, in the years of 2008 and 2009, compared to the lower premiums in earlier years. For instance, for CS (UBS) we obtain a maximum value of 21.3 (12.7) bn CHF in 2008. This is the premium the bank has to pay for debt insurance for one year. Although these numbers seem to be large, compared to profits, because it is questionable whether one of the banks could have afforded the premium payments in this time of distress, one has to take into account the reduced interest payments to depositors which would disburden the banks on the other side. The

[1] Per definitionem, it is impossible to determine the value of the implicit guarantee, because the intervention is uncertain and the implementation is unspecified.

reason for this reduction is that the liability insurance induces a riskless bond to debtholders who would have asked for higher risk premiums in this market situation. In the concrete case of UBS, many creditors even withdrew their deposits. On the other hand, the guarantee values seem to be low compared to the total insured liabilities. However, realistic loss given defaults are much smaller than total amounts of insured debt. Additionally, we observe a decline in the guarantee value for the UBS after the bailout in October 2008. The sensitivity of the results with respect to different model specifications and parameters, e.g., jumps in the asset path or various volatility levels, is analyzed. We conduct a policy analysis with respect to political and regulatory relevant and frequently discussed measures, such as increased capital requirements or an augmented number of audits. Strengthened capital requirements and the increased number of audits reduce the guarantee value substantially.

The paper is organized as follows. Section 2 provides the conceptual framework clarifying the term implicit guarantee by differentiating it from the concepts of no or an explicit guarantee. Moreover, we give an overview of the Swiss situation and describe the key figures of UBS and CS. Section 3 discusses the existing literature. Section 4 is devoted to our model. Section 5 explains our data and the parameter specification for the benchmark scenario and presents the results. In section 6, we analyze our model with respect to policy relevant parameters. Section 7 concludes.

2 Background

2.1 Terminology

To clarify the term implicit guarantee, we describe the two extreme cases of no guarante and an explicit guarantee. We then discuss the gray area 'in between', which we call implicit. We assume that the guarantor is free of default risk.

Figure 1 depicts the situation of a bank without a guarantee. We observe the usual concept: debtholders receive the riskless rate and an adequate risk premium for the default risk of the bank. We assume that shareholders have a limited liability, i.e., shareholders lose the invested capital in default. Note that this case only occurs for institutions which are not 'too big to fail' or not systemic relevant for another reason. We present the case of an explicit guarantee for debt in Figure 2, since our paper focuses on liability insurance. Explicit means that the bank and a guarantor agree about the risk transfer on a contractual basis, such that the bank is able to offer a riskless bond. Hence, debtholders are not exposed to the default risk of the debt issuing bank. In contrast, the guarantor has to bear the losses. However, she requires an appropriate insurance premium. Shareholders have a limited liability, which implies that the bank is eliminated after default. Figure 3 illustrates the case of an implicit guarantee. We call the guarantee implicit if there does not exist a contract between bank and guarantor, although

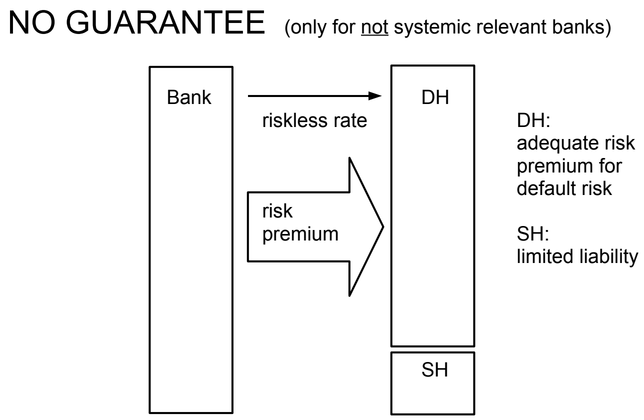

Figure 1: No guarantee: debtholders (DH) obtain default risk-adequate premium, shareholders (SH) are liable with the invested capital

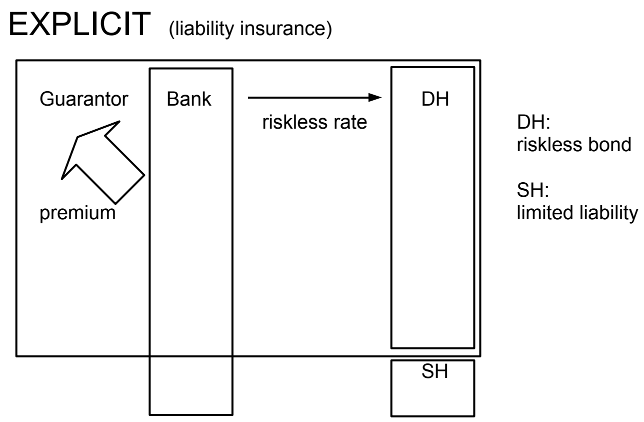

Figure 2: Explicit guarantee: guarantor insures debtholders (DH) against losses in default, DH have a riskless bond, shareholders (SH) are liable with the invested capital

there are reasons to assume that a guarantee exists.[2] Therefore, the intervention is uncertain and the implementation is not specified. The uncertainty of the intervention is represented by the dashed line and is, for example, affected by the perception of systemic relevance and the ability of the guarantor to afford the bailout. In Switzerland, CS and UBS are both assumed to be 'too big to fail'.[3] This implies that both banks enjoy an implicit guarantee, where an intervention is relatively certain. This fact was proven for UBS in October 2008. Generally, debtholders and shareholders benefit from the potential guarantee. For instance, the bailout of UBS avoided the bankruptcy of the institution and protected shareholders from a total loss and debtholders from

[2]It is possible that market participants suppose that a bank is systemic relevant and has an implicit guarantee before default. But the guarantor may decide to let the bank go bankrupt in default. In this case, the implicit guarantee exists until default, in our terminology.

[3]See page 16, Schlussbericht der Expertenkommission zur Limitierung von volkswirtschaftlichen Risiken durch Grossunternehmen, 4. October 2010.

damages in the case of a default. We previously noted the hereby also induced market discipline problems. Additionally, debtholders receive a reduced risk premium, because of the anticipation of the guarantee. Supplementary, shareholders profit from reduced refinancing costs of the bank because of the implicit guarantee. One may argue that banks transmit their refinancing benefits on to credit users, although it is debatable (see Passmore (2005)). The actual allocation of these benefits depends on the form of the intervention (for instance, expropriation of shareholders or capital injection) and frictions between the stakeholders (for instance, the partial transmission of funding advantages). However, shareholders, debtholders and borrowers profit by the implicit guarantee, whereas the guarantor receives no premium. In other words, the more likely the rescue, the more grants the guarantor a subsidy.

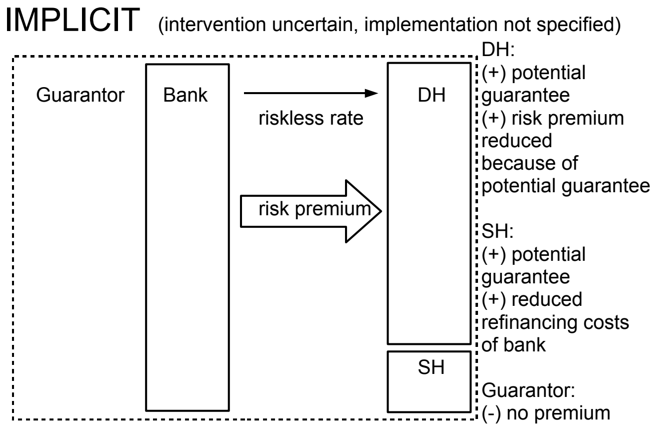

Figure 3: Implicit guarantee: debtholders (DH) and shareholders (SH) benefit from potential bailouts; the guarantor does not receive a premium

As aforementioned, CS and UBS enjoy an implicit state guarantee. Our goal is to compute the premiums for debt insurance of these two banks from 2004 until 2009, as if the guarantee had been explicit.

2.2 Swiss situation

In this section, we briefly describe the prominent and pivotal role of the financial industry as a whole and of UBS and CS for the Swiss economy in particular. As illustrated in Table 1, 12.70% of the GDP of Switzerland is created by the financial industry. We note that this number does not reflect the additional indirect value for the real economy through a financing infrastructure provided by such a pronounced and diversified financial industry, especially for an export oriented economy like Switzerland. UBS has 1340.5 bn CHF of total assets (end of 2009) and about 26 thousand employees. Hence, it is the largest bank in Switzerland. The bank is the biggest asset manager worldwide (over 2000 bn CHF assets under management). Although one UBS branch originates in 1747, the current structure and size are founded in the merger of the Union Bank of Switzerland and the Swiss Bank Corporation in the year 1998, as well as the acquisition

Table 1: Employment and economic value creation of the financial industry in 2006 for Switzerland

	Employment		**Economic value creation**	
	absolut	in percent	absolut (in mio CHF)	in percent (of GDP)
Banking industry	113'000	3.60%	40'735	9%
Insurance industry	48'000	1.50%	16'717	3.70%
Affiliated operations	23'000	0.70%	n.a.	n.a.
Financial industry	183'000	5.80%	57'551	12.70%

Source: Swiss Federal Department of Finance: Situation und Perspektiven des Finanzplatzes Schweiz, Swiss Federal Statistical Office

of the US brokerage firm PaineWebber in 2000. Besides UBS, the other global financial player, namely CS (1031.4 bn CHF of total assets and 1229 bn CHF of assets under management), employs more than 20 thousand people in Switzerland. More than 30% of bank lending to domestic small and medium sized enterprises (SMEs) is provided by the two institutions. In former years, about 3-5% of the Swiss GDP was created by UBS and CS.

In Figure 4, the development of total assets of both banks and of the Swiss GDP during the last years is illustrated. The massive increase and decrease of the UBS's balance sheet length is striking. From 2003 to 2006, the sum of total assets of UBS and CS grew by 162%, a value of 1382 bn CHF.

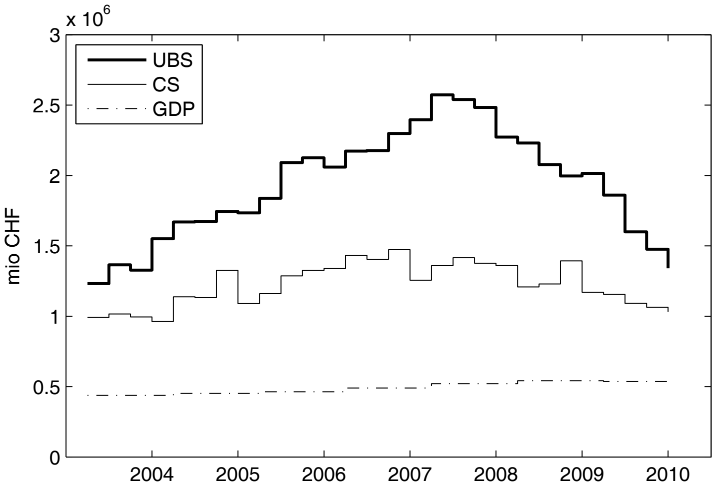

Figure 4: Asset development of UBS and CS

This was nearly the eightfold GDP up to the end of 2007, which is an exceptional relation with respect to international standards. During the subprime crisis, the two big banks, especially the UBS, were hit hard[4] by the crisis. Both banks took measures to strengthen their resilience,

[4]During Q3 2007 up to Q1 2009 UBS losses accumulated up to 63 bn CHF.

e.g., reducing risky positions, the overall size of trading portfolio and balance sheet. They raised sizeable amounts of capital, for example, UBS raised capital in the early stages of the crisis. However, in October 2008, it became necessary for the government to intervene. The primary element of the rescue package for the UBS, put together by the Swiss government, the Financial Market Supervisory Authority (FINMA) and the Swiss National Bank (SNB), was the possibility for the bank to transfer up to $60 bn of illiquid assets to a special purpose vehicle of the central bank to facilitate their orderly liquidation. The Swiss government subscribed to mandatory convertible notes in the amount of 6 bn CHF, and hence, strengthened the bank's capital base.

2.3 Literature review

In this section, we provide a selective review of the literature. First, the different approaches for determining the size of the guarantee primarily relevant for our work are presented. Then, we document empirical evidence of market responses to the TBTF status of banks. Finally, we briefly describe some of the theoretical approaches to describe the potential consequences of government guarantees on market discipline or risk-taking.

The literature in the research on valuing loan or deposit guarantees is extensive. We cannot present it completely. We identify two primary strains of the literature: *contingent-claim* and *market-based analysis*. In the latter valuation method, traded securities with and without guarantees are compared. The price difference between these securities is interpreted as the implied value. Hsueh and Kidwell (1988) study municipal bonds, which received a credit guarantee from the state government resulting in a raise of the credit ratings of all bonds to the highest category. Not surprisingly, they find that the savings in interest were the highest for bonds with very low ratings before the credit enhancement. Passmore (2005) calculates the implicit guarantee value to F&F (shareholders and homeowners) using a cash-flow approach. He estimates gross subsidies from the borrowing advantage by comparing yields on financial corporate debt and debt of a GSE. Baker and McArthur (2009) investigate the spread between the average cost of funds for small banks and the cost of funds for systemic relevant institutions with assets in excess of $100 bn. They find that the gap widened in the period from the fourth quarter of 2008 through the second quarter of 2009, after the government bailouts largely established 'too big to fail' as an official policy. The evaluation of loan insurance using contingent-claim models is based on the initial work of Merton (1977, 1978), following his research on corporate debt pricing (Merton (1974)) by applying option pricing theory. Merton (1977) derives an options-based formula to evaluate the cost on the guarantor for issuing a guarantee of bank deposits. This pricing model is built on the isomorphic correspondence between deposit insurance and common stock put options. The payoff-structure of the loan guarantee at the maturity date of the bond is identical to that of a European put option. Therefore, the Black and Scholes' (1973) option pricing techniques can be applied. Merton (1978) extends the earlier framework taking into account explicitly surveillance costs and random auditing times. These additional default checkups are an important feature used to make the model more realistic. It is unreasonable to interpret debt as a European put option with a maturity of 5 years without any audits and detections of default in the meantime. Ronn and Verma (1986) use time series data on the variance and market value of bank's equity, as well as the book value of its debt, to infer the underlying variance and value of assets and then arrive at a point estimate of the appropriate deposit premium from the put's value. Giammarino, Schwartz, and Zechner (1989) incorporate bankruptcy costs, suggesting that it might be optimal for the auditor to not immediately force a bank to stop operations if the asset value reaches the value of liabilities. They adapt the framework to Canadian banks. Dermine and Lajeri (2001) anticipate the risk characteristics from the lending function of banks and show that conventional insurance premiums underestimate the fair value. The implicit guarantee value and corresponding risk of F&F is also studied by Lucas and McDonald (2006, 2009) using a contingent-claim framework analogue to Merton (1978) incorporating audits during maturity. Guarantee value, risk neutral and actual default probabilities are computed via Monte Carlo simulation and compared to the results with varying variables including asset volatility, capital requirements, exogenous growth, monitoring frequency and debt adjustment rules.

The seminal papers of O'Hara and Shaw (1990) and Flannery and Sorescu (1996) investigate different market effects in connection with the financial crisis, where the Continental Illinois Corporation was involved in July 1984. The former authors investigate equity prices before and after the Comptroller of the Currency testified that some banks were simply TBTF and that total deposit insurance would be provided for those banks. Using an event study, they report an average 1.3% abnormal return to common equity of TBTF banks. In contrast, Flannery and Sorescu (1996) ask whether banks' debtholders were rationally pricing bank-specific risks during 1983-1991. In a panel regression analysis, they find that when government's willingness to insure bank holders of subordinated notes and debentures (SNDs) declined over time[5], debenture yields reflected the specific risk of the banks as leverage and asset quality. Therefore, investors became more diligent about pricing default risks when authorities stopped protecting financial institutions.[6] Morgan and Stiroh (2005) revisit the Continental case focusing on the relationship between TBTF bond spreads and risk relative to other banks. In particular, they argue that spreads and ratings will differ to the extent that investors and rating agencies disagree about the probability of government support where they make the assumption that investors use ratings as a proxy for risk. Their findings suggest that also the Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991, which limits regulators' discretion to support distressed relevant banks[7] did not entirely shake investors' beliefs in TBTF, which put the results of Flannery and Sorescu (1996) a bit into perspective. Rime (2005) also uses bank ratings to test the

[5]For instance, in 1991, debenture holders suffered losses when the Bank of New England or Southeast Banking Corporation went bankrupt.

[6]Also Avery, Belton, and Goldberg (1988) analyze the relation between default risk premium on SNDs and accepted measures of bank risk for the years of 1983 and 1984. They find no relationship. Few reasons for this result are provided in Flannery and Sorescu (1996).

[7]For details about the FDICIA, especially in the context of the TBTF discussion, see the review of Wall (2010) and references therein. This article was originally published in 1993, but due to the current crisis and discussion was reprinted in 2010.

presence of TBTF expectations, but these exclusively for the years of 1999-2003. Rating agencies distinguish between issuer rating, that also considers possible external support, and individual rating, that focuses on the intrinsic capacity of a bank for debt repayment. Therefore, the difference should also reflect the TBTF status of a bank. In a regression analysis, he finds that variables, like total assets or market share, characterizing the TBTF status of a bank have a positive and significant effect on the rating difference. Hence, any implications regarding the impact on market discipline is dependent on the degree that market investors incorporate these ratings into their investment decisions. Völz and Wedow (2009) examine the same question, but consider investors on the credit default swap (CDS) market, i.e., the authors quantify the potential distortion due to the TBTF expectation on CDS prices in 24 countries during the years of 2002-2007. Their findings confirm that the spreads reflect banks' risk and also a size distortion. Spreads tend to be lower for banks with a larger size, relative to home country's gross domestic product. The consequences of the bailout policies on financial institutions, which are not TBTF, are studied in the paper of Gropp, Hakenes, and Schnabel (2010). The authors show that the risk-taking of banks outside the safety net increases significantly in the presence of TBTF institutions. The argument is that institutions with an implicit guarantee benefit due to lower refinancing costs, which enables them to offer more attractive conditions for depositors, or obligors, with higher deposit or lower loan rates, respectively. Consequently, the fiercer competition brings unsecured institutions to take riskier positions.

Though not directly relevant for our work, we provide a very selective overview of the recent theoretical literature about market distortions created by government interventions in the financial sector. Cordella and Yeyati (2003) develop a framework in which the ex-ante announced commitment of the authorities to bail out insolvent banks in certain unfavorable states of nature induces a lower equilibrium risk level. A bailout is here 'not to withdraw' the bank license and payment of the outstanding liabilities in the case when the bank is not able and not willing via recapitalization to meet its liabilities. In general, the potential bailout generates two opposite effects: a market discipline problem and the so called value effect. On the one hand, the probability of surviving depends less on the bank's choice of risk and more on the supervisory authority's action, therefore, shareholders have an incentive to choose riskier asset portfolios for maximizing expected profits, which of course, also increases the default risk. On the other hand, governmental guarantees naturally increase the survival probability and future rents due to lower refinancing costs, thus raising the charter value in the case of a default, which, in turn, generates the incentive to protect it by reducing the asset portfolio risk. In the theoretical part of their paper, Ennis and Malek (2005) analyze the impact of deposit insurance (full and partial coverage), TBTF policy and the interaction of both on the banks' decision process to attract depositors. The authors also make the assumption of a probabilistic bailout ('constructive ambiguity'), which is dependent on a bank's size. The bailout itself is specified that all deposits beyond the deposit insurance system are covered. One of the main policy implications they can draw is that a tougher intervention regime, i.e., lower bailout probability for all bank sizes, induces the reduction of the equilibrium bank size and risk level.

3 Model

Based on the insights of Merton (1977), we use an option pricing approach for computing UBS' and CS' implicit guarantee. The idea is to evaluate such insurance as a European put option on the underlying UBS or CS assets with maturity date of debt and with the future book value of debt as the strike price. We compute the put option price via Monte Carlo simulation. In accordance with Lucas and McDonald (2009), we incorporate negative jumps $-\phi \leq 0$. For a standard Brownian motion W and a Poisson process N with intensity μ, the dynamics of the asset paths are defined via

$$\frac{dA_t}{A_{t-}} = (r_f + g_t - \delta\frac{E_0}{A_0} + \mu\phi)dt + \sigma_A dW_t - \phi dN_t$$

which yields the risk neutral discrete time formula

$$A_{t+h} = A_t \exp\left((r_f + g_t - \delta\frac{E_0}{A_0} - \frac{\sigma_A^2}{2} + \mu\phi)h + \sigma_A\epsilon\sqrt{h}\right)(1-\phi)^{N_h} \tag{1}$$

where h is the time step, A is the asset and E denotes equity. Subscripts represent time. r_f is the risk-free rate, g_t is the externally financed asset growth, δ is the dividend yield on equity, $\delta\frac{E_0}{A_0}$ is the dividend yield on assets, σ_A is the volatility of the assets and $\epsilon \sim \mathcal{N}(0,1)$ is standard normally distributed. The process N counts the number of jumps. If a jump occurs, we obtain $A_t = (1-\phi)A_{t-}$. The term $\mu\phi$ corrects the drift for the average effect of jumps. If we neglect the terms of magnitude $o(dt)$, the probabilities of the occurrence or the absence, respectively, of a jump in the interval between t and $t+dt$ are μdt or $1-\mu dt$, respectively. In formulae:

$$\mathbb{P}[N_{t+dt} - N_t = 1] = \mu dt$$

and

$$\mathbb{P}[N_{t+dt} - N_t = 0] = 1 - \mu dt.$$

Hence, it is a reasonable approximation to assume a Bernoulli distribution for the occurrence of jumps between t and $t+dt$.

Since the initial market value A_0 and volatility σ_A of the assets are not directly observable, we use the following equations which are based on Merton's framework and which are solved simultaneously for A_0 and σ_A :[8]

$$E_0 = A_0 e^{-qT} N(d_1) - L_0 e^{-r_f T} N(d_2) + A_0(1 - e^{-qT}), \tag{2}$$

$$\sigma_A = \sigma_E \frac{E_0}{A_0}\left(N(d_1)e^{-qT} + (1 - e^{-qT})\right)^{-1}, \tag{3}$$

[8]The last term $A_0(1-e^{-qT}) = \int_0^T qA_0 e^{-qt}dt$ in the first equation represents the accumulated dividend payments.

$$d_1 = (\log(A_0/L_0) + (r_f - q + \frac{\sigma_A^2}{2})T)/(\sigma_A\sqrt{T}),$$
$$d_2 = d_1 - \sigma_A\sqrt{T}$$

where T is the maturity of liabilities, L_0 is the strike price (initial book value of liabilities) and $q = \delta\frac{E_0}{A_0}$ is the payout rate of assets. Thus, we again use option pricing theory since equity can be valued as a call option. The two advantages of this method are first, that one can avoid to directly estimate the outstanding market value of the complex liability structure and second, one does not have to use traded debt prices which already reflect the value of the implicit guarantee.

We assume the following evolution of the book value of liabilities L which adjust towards a target liability to asset ratio at several different adjustment rates:

$$L_{t+h} = L_t e^{(r_d+\gamma g_t)h} + \mathbb{I}_t\alpha_t h(\lambda^* - L_t e^{r_d h}/A_t)A_t \tag{4}$$

where α_t denotes the annual rate of adjustment, λ^* is the target liability to asset ratio, $\mathbb{I}_t$ is an indicator variable that equals 1 in a period where liabilities are adjusted and 0 otherwise, r_d is the growth rate of liabilities to cover promised coupons and γ is the fraction of externally financed growth supported by debt. At some pre-specified dates we allow for audits which examine if the asset liability ratio falls below the default trigger. If this case occurs, asset and liability processes are stopped, i.e., the values are held constant and multiplied with the appropriate discount rate until maturity. At maturity, we collect the put option payoffs $\max(L_T - A_T, 0)$ of all paths and compute the put price as the expected discounted payoff.

For the correct interpretation of the put option price it is crucial to emphasize the important role of the maturity. We suppose that all debt has a maturity of time T which is a strong assumption. In order to get reasonable and realistic results, one calculates the mean of all the different maturities provided by the bank. However, one has to be aware of the fact that the put option price represents the state guarantee with respect to debt and deposits with maturity T.

4 Benchmark scenario

4.1 Data and parameter specification

All initial firm specific values for our simulation are reported in the Tables 4, 5 and 6 in the Appendix. As described previously, the initial market value of the assets and asset volatility can be inferred by solving equations (2) and (3), where we choose the sum of the initial market value of equity and the book value of liabilities as a first guess for the market value of the assets A_0.[9] The benchmark scenario does not include jumps. The risk free rate is the Switzerland government

[9]We exploit the MATLAB routine `lsqnonlin` and ensure that A_0 and σ_A are in the same range.

bond yield (with respective maturity).[10] For the dividend yield q we use the respective annual yield for all quarters. Moreover, we employ the historical equity volatility, calculated as a rolling 63-day annualized standard deviation of equity price changes. Time to maturity T is set to one year, since we are interested in determining the guarantee value for one year. Here, we assume that debt is homogenous with a maturity of one year. This is a strong assumption, recognizing that the debt structure of these banks is diversified with a variety of maturities. With more information about the maturity structure, one could use the average maturity to carry out the calculations. Later, we discuss the five year case to illustrate the size effects of this change. In Figure 5, historical equity and corresponding asset volatilities of UBS and CS are plotted. Not surprisingly, the volatility level is moderate up to the end of 2006. The second part of our considered time period is characterized by great uncertainty expressed in asset volatility up to 7% in 2008. The simulation of the asset and liability path (equations (1)

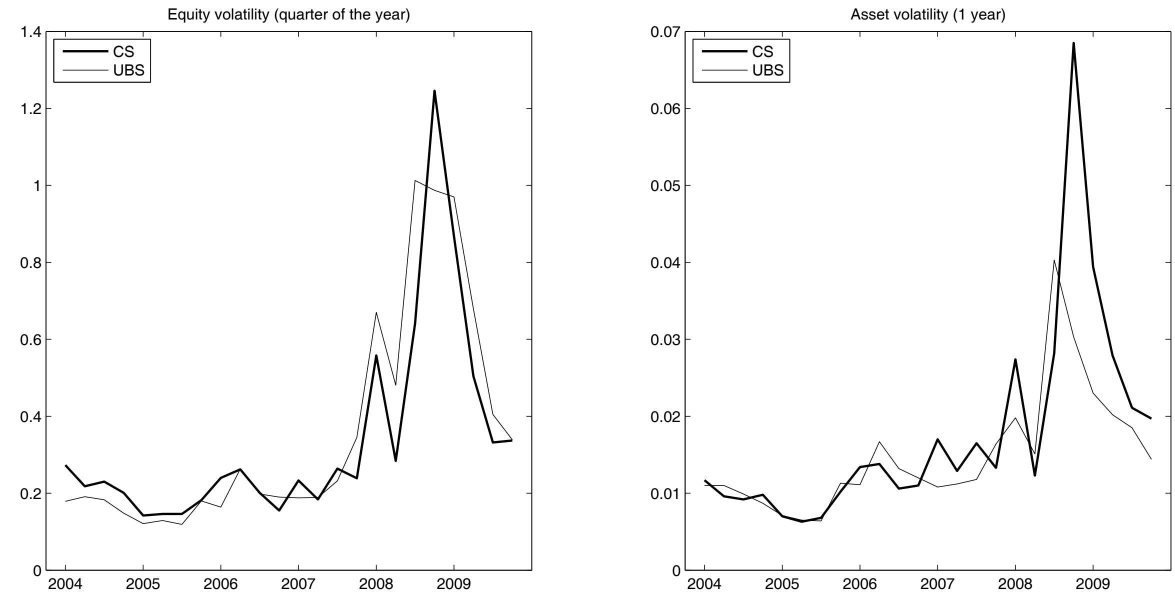

Figure 5: First panel: equity volatility calculated as a rolling 63-day annualized standard deviation of equity price changes. Second panel: model implied asset volatility with a debt maturity of one year

and (4)) requires the specification of other parameters. The asset growth rate is determined by the logarithm of the difference in total assets.[11] Therefore, we adjust the asset growth rate dynamically at every starting point based on the average growth rate of the last year by taking into account the changing market conditions. A growth rate based on the long time average would have drastically failed in the UBS case, where the balance sheet length roughly halved during the years 2008 and 2009. The promised return on debt is determined by the fraction of annualized interest rate expenses over the outstanding liabilities of the last quarter. We then fix some parameter values for both banks (see Table 2), a procedure that is quite similar to that

[10] The treasuries are called 'Obligationen der Eidgenossenschaft'.

[11] In formula: $log\left(\frac{\text{Total Asset}_t}{\text{Total Asset}_{t-1}}\right)$ averaged over the last four quarters.

in Lucas and McDonald (2006). It gives us the opportunity to compare our results and check them regarding consistency.

Table 2: Parameter values for both banks and for all starting times in the benchmark scenario

Name	**Value**
Jump intensity and size	0
Target liability to asset ratio	0.92
Debt proportion of external financing	1
Adjustment of liabilities to higher target	0.8
Adjustment of liabilities to lower target	0.4
Frequency of updating debt	252
Default trigger	1
Frequency of checking bankruptcy trigger per year	4
Time steps per year	252
Time to maturity	1y
Number of Monte Carlo simulations	40000

The target liability to asset ratio is set according to the Basel II framework to 92%, where we are aware of the fact that Basel incorporates risk weighted assets or stressed recovery values to fix the capital requirements. It is assumed that asset growth is completely externally financed by debt. Liabilities adjust gradually and asymmetrically.[12] The 80% annual adjustment up versus 40% annual adjustment down reflects the difficulty for a financial institution to deleverage in times when asset values are declining. For the default trigger, based on the asset value relative to book liabilities, we begin with a value of 1, which is checked four times annually. This is in line with the current Swiss regulatory framework[13], where banks inform the Swiss Financial Market Supervisory Authority (FINMA) quarterly about their capital resources. Since we obtain the equity volatility based on daily data, we also run the simulation with 252 time steps annually. To include stressed markets, Lucas and McDonald (2006) raise volatilities by four times its normal level when assets fall to 101% of liabilities, taking into account increasing volatilities during these times. We assume this procedure occurs over the period of moderate market conditions (2004-2007). In turbulent times (2008-2009), we adjust this approach by halving the volatility when assets increase to 110% of the liabilities. The identification of financially stressed, or unstressed, times takes place in every time step of the simulation.

4.2 Results

The results, namely guarantee value, value at risk (VaR) at a confidence level of 95% and the corresponding expected shortfall (ES) for CS and UBS with respect to one year over the time period 2004 to 2009 (quarterly) are reported in Table 3. The first two years are characterized by values almost all equal to zero. During 2006 and 2007, the guarantee value and VaR are also

[12] In equation (4) we set $\mathbb{I}_t \equiv 1$. Hence, the liabilities are adjusted in each time step, which is typically each day.

[13] See Article 13, ERV (Eigenmittelverordnung).

quite low, where we first note that it is reasonable to calculate the ES considering the tail risk. Second, the increasing numbers for the ES in the last two quarters of 2007 can be linked to the start of the subprime crisis with rising market uncertainty. In Figures 6 and 7, we present the guarantee value development in connection with firm specific events. Although we are aware of the limitations of our approach, particularly a comparison of CS and UBS in the third and fourth quarter of 2008 is remarkable. Up through the bailout on October 16th in 2008, the insurance premiums for UBS were higher than for CS. In the fourth quarter of 2008, all measures for UBS roughly bisect and had lower values than CS for the rest of the considered period. We think that this risk reduction can be partly explained by making the implicit state guarantee certain throughout the bailout. The contrary and high level values for CS, where, e.g., the ES in the fourth quarter of 2008 is five times higher than in the third quarter and the put price for CS in the fourth quarter is less than twice as high as the UBS value in the third quarter, are puzzling. An explanation is the increasing uncertainty on the CS side (see also Figure 5) – possibly increased since, at this point in time, the situation at the bank was not clear as well as whether Switzerland could have afforded another bailout. Note, the results are dependent on market variables, like market capitalization of equity and equity volatility. Both quantities are determined by the market risk perception, and therefore, are also influenced by the implicit state guarantee, which is anticipated by market participants, to some extent. We suppose that, for instance, the observed market capitalization of equity would be lower without an implicit guarantee. Hence, the premiums would be higher for the banks.

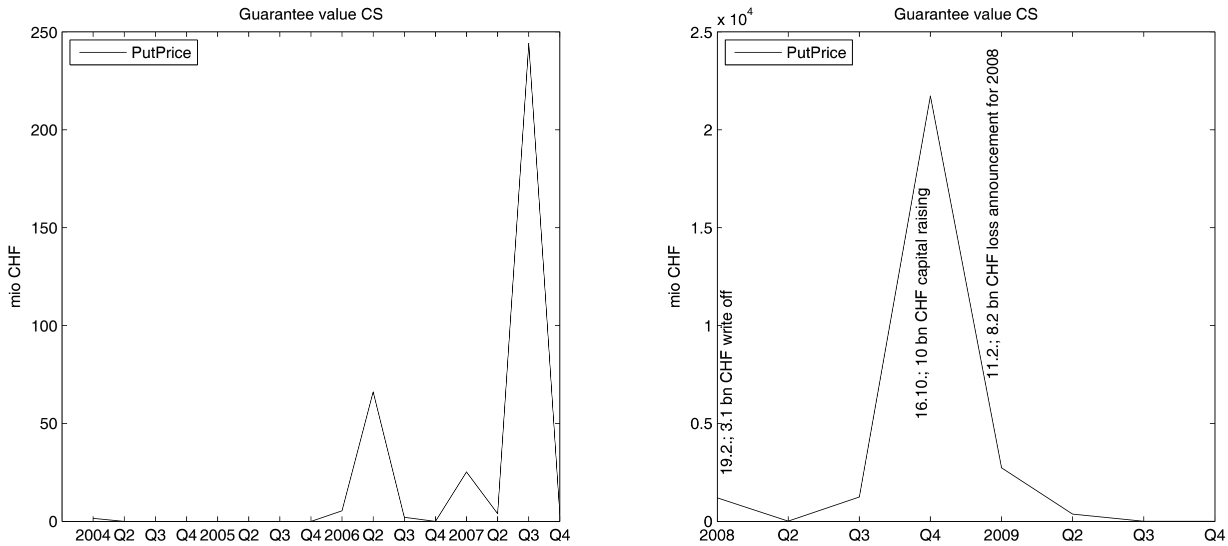

Figure 6: Guarantee value CS in the benchmark scenario (mio CHF). The text modules document the most important firm-specific events

5 Sensitivity and policy analyses

In this section, we check the robustness of our results with respect to changes in volatility and time to maturity and investigate the political relevant monitoring measures leverage ratio and

Table 3: Results of the benchmark scenario. All values for the guarantee value (put price), value at risk (VaR) at a confidence level of 95% and corresponding expected shortfall (ES) are reported in mio CHF.

	CS			UBS		
Time	**Guarantee value**	**VaR** (95%)	**ES**	**Guarantee value**	**VaR** (95%)	**ES**
2004 Q1	0	0	30	0	0	0
Q2	0	0	0	0	0	0
Q3	0	0	0	0	0	0
Q4	0	0	0	0	0	0
2005 Q1	0	0	0	0	0	0
Q2	0	0	0	0	0	0
Q3	0	0	0	0	0	0
Q4	0	0	10	0	0	0
2006 Q1	10	0	160	0	0	0
Q2	70	0	1440	188	0	3781
Q3	0	0	40	7	0	135
Q4	0	0	0	9	0	179
2007 Q1	20	0	500	13	0	254
Q2	0	0	90	39	0	778
Q3	240	0	4730	345	0	6931
Q4	0	0	70	268	0	5377
2008 Q1	1170	9000	19960	2033	16325	31380
Q2	10	0	170	224	0	4504
Q3	1230	8370	21880	12682	73088	98144
Q4	21340	93860	117830	5173	38183	57373
2009 Q1	2770	21860	36390	1402	9980	24527
Q2	380	0	7610	192	0	3852
Q3	0	0	70	2	0	33
Q4	0	0	40	0	0	3

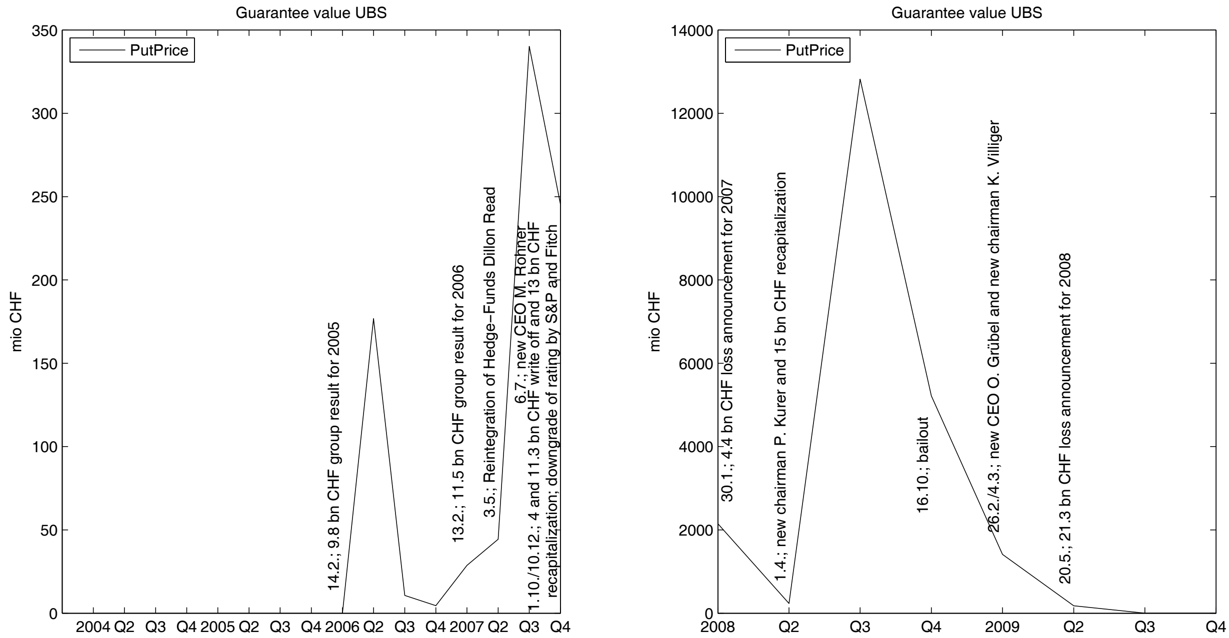

Figure 7: Guarantee value UBS in the benchmark scenario (mio CHF). The text modules document the most important firm-specific events

number of audits. The latter explorations are highly important for regulatory implications.

5.1 Jumps

Our benchmark case assumes continuous asset paths. To introduce stress situations in the form of price drops on the asset side, we compute the guarantee values of CS and UBS for several discontinuity scenarios of the asset path. As described in the model section, we incorporate negative jumps if the two parameters ϕ and μ are positive. Tables 7 and 8 present the liability insurance premiums for one year and the corresponding expected shortfalls for the (annualized) intensities $\mu = 252 * 0.004 = 1.008$ and $\mu = 252 * 0.001 = 0.252$, respectively, and jump sizes of $\phi = 0.01$ and $\phi = 0.05$, respectively. Hence, we investigate daily jump probabilities of 0.4% and 0.1% and collapses of the asset path of 1% and 5%.

First, we observe that jumps, i.e., the anticipation of plunges on the asset side, generally have a substantial augmenting impact on guarantee values. Second, increasing the jump size leads to remarkable increases in the values. For example, guarantee values for UBS are zero for $\phi = 0$ (benchmark case) and $\phi = 0.01$ in the first quarter of 2005, whereas they achieve values of 1.8 bn CHF and 8.33 bn CHF for jump sizes of 5%. Third, the effect of increasing intensities is also observable: guarantee values are generally greater with higher intensity. Fourth, the impact of jumps is enormous in the years of 2004 through 2007, before the crisis. They are moderate during the turbulent times in the years of 2008 and 2009. The reason for this result are different volatility adjustment regimes for different market situations in our model, which are described in the data and parameter specification subsection and intend to avoid unrealistic volatility values.

In summary, our results yield a clear monotonic relationship between jump size and intensity, on the one hand, and guarantee values, on the other hand. More specifically, the higher the expected negative jumps or the greater the intensity of the jumps, the higher the guarantee values.

5.2 Volatility

Figures 8 and 9 illustrate the sensitivity analysis of the guarantee value with respect to the asset volatility. The shaded area represents the put price for one year for different asset volatilities between 0.9 and 1.1 times the benchmark volatility.

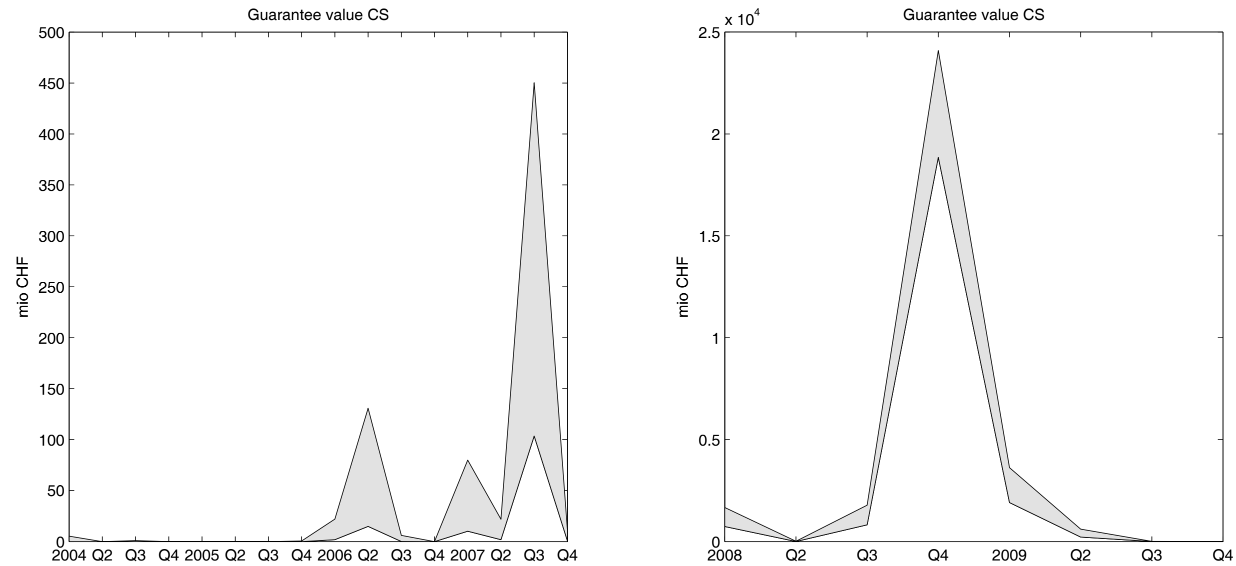

Figure 8: Guarantee value CS and deviation caused by changes in asset volatility. The area plot illustrates the guarantee value for asset volatilities between 0.9 and 1.1 times the ones induced by the benchmark scenario

In 2008, the difference of the guarantee value induced by the low (-10% compared to the benchmark case) and the high (+10%) asset volatility is at most 5 bn CHF for both banks and up to one third of the high value in percentage for UBS. In previous years, the difference of at most 500 mio CHF is much smaller in absolute terms. However, the high guarantee value is 4.5 times larger than the low one for CS in the third quarter of 2007. Thus, we find that the put price is more sensitive in percentage terms to asset volatility variations before the crisis than in turbulent times.

Having discussed the effects of an asset volatility band width around the benchmark, we also want to describe alternative specifications for the historical equity volatility, which influence the estimation of the asset volatility. We decided to incorporate the last quarter of equity price changes for calculating the benchmark volatility, because we also determine guarantee values quarterly, therefore always using a new information set without overlap. However, other time

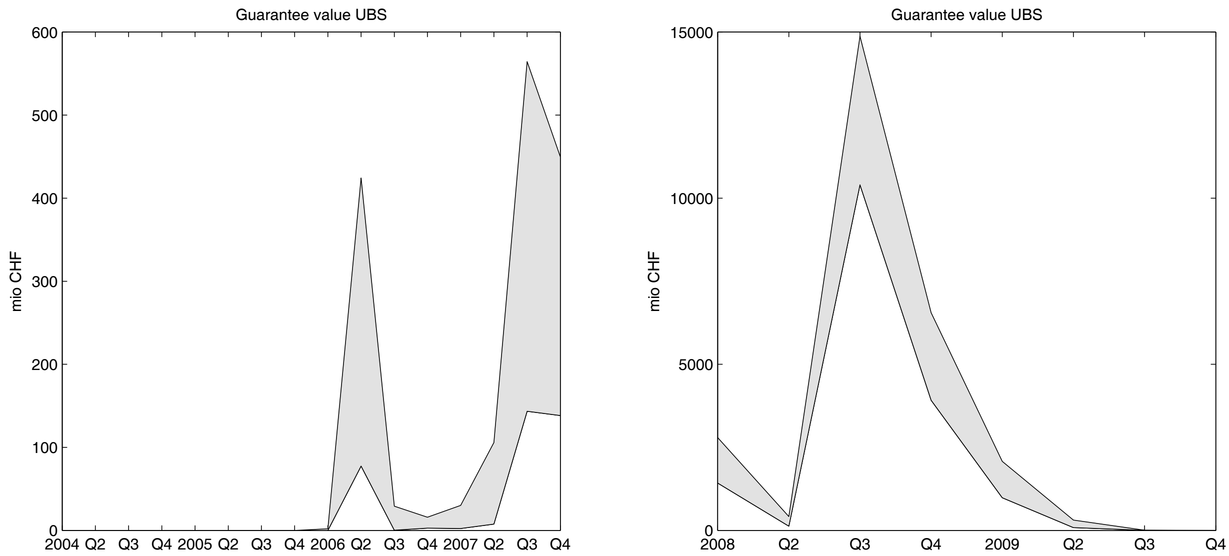

Figure 9: Guarantee value UBS and deviation caused by changes in asset volatility. The area plot illustrates the guarantee value for asset volatilities between 0.9 and 1.1 times the ones induced by the benchmark scenario

intervals are possible. We report the numerical values for a rolling 10-, 63-, 126- and 252-days window for both banks in Table 9 in the Appendix. In Figure 10, we see the corresponding premium evolutions for CS.[14]

As expected, longer time horizons naturally smooth the premium development, since erratic changes become less important, but more persistent, with a longer time horizon. This effect is readily identifiable on the right side of Figure 10. The peak of the premium evolution moves from the third quarter of 2008 to the second quarter of 2009 on a diminishing level, where the relative changes are less dramatic. In the benchmark case, the premium drops after reaching the maximum by about 88%, whereas the decline for the 252-day horizon occurs nine months later and is just about 65%. If we compare the premiums integrated for the years 2004-2009 across the volatility specifications (see Table 9) we observe, for both banks, a bisection of the benchmark amount with the 252-days calculation horizon.

5.3 Maturity

In the benchmark scenario, we assumed a homogenous debt structure for both banks with a maturity of one year. We indicated that we have no information about the maturity structure of the liability side of these institutions.[15] Therefore, we discuss the case where debt maturity is elongated to five years. The bank is also insured for the same period. In the Appendix, Table

[14]We depict here only the bank CS, because the UBS value in the third quarter of 2008 for the 10-day window reached a high level, which distorts the graphical illustration.

[15]In Lucas and McDonald (2006), it is assumed that debt with an average maturity of 2.65 years (for Fannie Mae) is rolled over for the studied guarantee period of ten years.

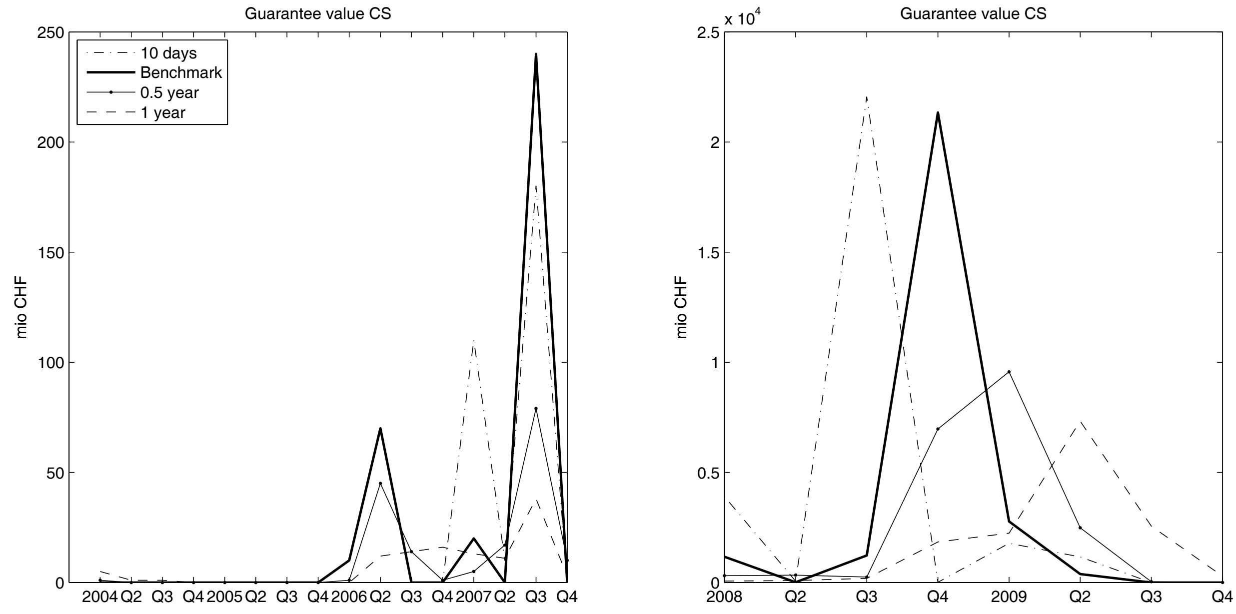

Figure 10: Guarantee values refering to a historical equity volatility respectively calculated as a rolling 10-, 63-, 126- and 252-days annualized standard deviation of equity price changes for CS

10, we report the results of the guarantee value and ES for both cases. The obtained guarantee values (ESs) range up to 170 bn (480 bn) CHF during the turbulent times, which is roughly the decuple of the benchmark scenario. These drastic changes can be explained by higher asset volatilities (solving equations (8) and (9)) and higher uncertainty due to the longer horizon.

5.4 Leverage ratio

A decrease of the target liability to asset ratio from 92% in the benchmark scenario to 90% is in line with the current discussion about strengthened capital requirements for banks in Switzerland and other countries. Table 11 in the Appendix presents the guarantee value and expected shortfall for the benchmark case and for the lower ratio. The result is highly relevant with respect to regulatory implications and illustrates that increased capital requirements significantly reduce the guarantee value for both banks. For instance, the largest value for CS in the fourth quarter of 2008 declines from 21.3 bn CHF in the benchmark scenario to 18.6 bn CHF. In the first and second quarter of 2007, the guarantee value for UBS diminishes even thirteen times, compared to the benchmark case.

As in the investigation of asset volatility, we find a similar phenomenon: the percentage differences between a target liability to asset ratio of 92% and 90% are larger in the years before the crisis. Leverage rates of CS and UBS were around 0.98 in terms of total assets. If we increase the target liability to asset ratio to 98%, we obtain maximum guarantee values of 33.3 bn CHF for CS in the fourth quarter of 2008 and 28.9 bn CHF for UBS in the third quarter of 2008. All values of the years 2004 until 2009 are presented in Table 11 and are substantially higher than in the benchmark case.

Although the result suggests stronger capital requirements, one has to be aware of the fact that the model does not consider the market for illiquid assets and the issue of 'fire sales' of these assets in times of financial distress, as discussed in Brunnermeier and Pedersen (2009), Cifuentes, Shin, and Ferrucci (2005). Hence, our model ignores funding and market liquidity risk, but focuses on solvency risk. The current crisis has shown that more rigorous liquidity measures are necessary. The liquidity aspects cannot be captured by this approach. Note that our results depend on the comparison of already established capital adequacy constraint regimes. The adjustment of stronger capital ratios needs time and the implementation has to occur in appropriate market situations. Hence, the model does not provide the optimal point in time of an increase in capital requirements.

5.5 Audits

In our benchmark scenario, the regulatory authority FINMA was assumed to check the bankruptcy trigger quarterly. This is the typical frequency during normal times. Here, we study the effects of an increasing number of audits. The authority is allowed to conduct monitoring on a daily basis, especially during a stressed market environment (see, for instance, EBK-Bankinsolvenzbericht 2008). We adapt the specification from the volatility adjustment. As soon as the asset path falls to 101% of the liabilities, the bankruptcy trigger is monitored, additional to the four audits annually. Thereby, we increase the number of audits and detect more defaults. But, the losses given default will be smaller, since the regulator is able to cut off rapidly growing losses. In Table 12, we can see the dramatically reduced values for the put price and ES. Especially during the years of the financial crisis, the effects are very pronounced, which indicates that the described boundary is undercut more often. The most extreme case can be observed in the fourth quarter of 2008, where the ES of CS decreased to 2% of the former value. This value is also only slightly higher than the guarantee value, i.e., the regulatory authority stopped the business more or less directly, because no bigger losses could accumulate.

6 Conclusions

We quantify the guarantee value for the liability side of UBS and CS in a dynamic setup from 2004 until 2009. The model is based on option pricing theory and the computations are conducted quarterly to obtain the guarantee value, the value at risk and the expected shortfall four times a year. We provide the results for time horizons of one and five years, i.e., we assume that debt has a maturity of one or five years, respectively, and that the deposit insurance will last during this time period. The results indicate zero premiums for 2004 and 2005. The high levels of the guarantee value, as of 2008, are up to 22 bn CHF for CS and 13 bn CHF for UBS in the benchmark scenario. Hence, the model clearly captures the current financial crisis, which became apparent in the beginning of 2007. However, already in 2006, the guarantee values for both banks start to increase, which may reveal the detection sensitivity of the model with respect to the upcoming financial turmoil. Interestingly, whereas the guarantee value for UBS is typically larger than for CS until third quarter of 2008 in the benchmark scenario, the value for CS is four times greater after the bailout of UBS in October 2008. We may explain this finding with the ability of the model to identify the governmental rescue of UBS. The policy analysis yields a reduction of the guarantee value with respect to increased target liability to asset ratio and stress-adjusted number of audits. Hence, our results support the regulatory measures applied and discussed in the current situation. The practical implementation of the deposit insurance with the obliged premium payments according to the calculated guarantee values is an open issue. First, the cyclical model obviously generates the highest values during crisis times, where banks are short of capital and therefore are possibly not able to pay the fees. Second, the low values during unstressed situations may not allow the insurer to accumulate sufficient reserves for the potential depositor bailout.

Finally, we refer to the topic of executive compensation. As long as the state provides an implicit guarantee to large banks, it is difficult to argue that only shareholders are allowed to be concerned about managers' compensation. Chesney, Stromberg, and Wagner (2010) find that incentives to take asset risk can be large compared to incentives to increase the value of assets even if CEOs are mainly compensated with stocks instead of stock options. Our work emphasizes the strong impact of asset volatility and hereby asset risk on the guarantee value. Hence, the reduction of risk-taking incentives in compensation packages may be a valid concern raised by the state in order to reduce the costs of an implicit guarantee.

Appendix A Tables

Table 4: Initial parameter values for UBS and CS

	2004 Q1	**2004 Q2**	**2004 Q3**	**2004 Q4**	**2005 Q1**	**2005 Q2**	**2005 Q3**	**2005 Q4**
UBS								
Total assets (million CHF)	1670033	1673807	1744630	1734784	1838823	2091062	2125162	2060250
Initial market value of equity (mio. CHF)	105857	98001	95812	103638	109838	108193	116732	131949
Dividend yield on equity	0.0309	0.0315	0.0315	0.0315	0.0315	0.0256	0.0256	0.0256
Book value of liabilities (mio. CHF)	1627825	1634096	1702919	1694472	1795077	2045642	2078587	2008307
Equity volatility (quarter of the year, 63 days)	0.179	0.191	0.183	0.148	0.121	0.129	0.119	0.18
Equity volatility (10 days)	0.216	0.131	0.202	0.114	0.093	0.101	0.165	0.11
Equity volatility (126 days)	0.166	0.188	0.187	0.167	0.137	0.125	0.124	0.153
Equity volatility (one year, 252 days)	0.189	0.178	0.179	0.177	0.163	0.146	0.131	0.139
Externally financed asset growth	0.0332	0.0291	0.0335	0.0171	0.0055	0.0136	0.0262	0.0294
Promised return on debt	0.0160	0.0169	0.0165	0.0171	0.0220	0.0261	0.0252	0.0268
Rating (UBS group, long term)	Aa2	Aa2	Aa2	Aa2	Aa2	Aa2	Aa2	Aa2
CS								
Total assets (million CHF)	1138196	1131684	1326755	1089485	1159711	1287169	1326755	1339052
Initial market value of equity (mio. CHF)	49124	49238	44209	53097	57294	55443	62181	75399
Dividend yield on equity	0.011	0.0314	0.0314	0.0314	0.0314	0.0299	0.0299	0.0299
Book value of liabilities (mio. CHF)	1102858	1096400	1083781	1053212	1121187	1249015	1288121	1296934
Equity volatility (quarter of the year, 63 days)	0.273	0.218	0.23	0.201	0.142	0.146	0.146	0.182
Equity volatility (10 days)	0.281	0.21	0.21	0.073	0.113	0.152	0.159	0.112
Equity volatility (126 days)	0.258	0.25	0.222	0.22	0.176	0.144	0.146	0.164
Equity volatility (one year, 252 days)	0.295	0.255	0.24	0.234	0.203	0.187	0.161	0.154
Externally financed asset growth	-0.00444	0.016349	0.018699	0.046514	-0.00633	0.003542	-0.00439	0.028523
Promised return on debt	0.016912	0.016549	0.017893	0.018838	0.020546	0.021844	0.023675	0.028162
Rating (CS group, long term)	Aa3	Aa3	Aa3	Aa3	Aa3	Aa3	Aa3	Aa3

Table 5: Initial parameter values for UBS and CS

	2006 Q1	2006 Q2	2006 Q3	2006 Q4	2007 Q1	2007 Q2	2007 Q3	2007 Q4
UBS								
Total assets (million CHF)	2173218	2176675	2299326	2396511	2572945	2539741	2484235	2272579
Initial market value of equity (mio. CHF)	150663	140729	156615	154222	149157	151203	127525	108654
Dividend yield on equity	0.0256	0.0297	0.0297	0.0297	0.0297	0	0	0
Book value of liabilities (mio. CHF)	2119797	2125149	2244623	2340736	2515183	2482343	2429846	2230043
Equity volatility (quarter of the year, 63 days)	0.164	0.263	0.198	0.19	0.188	0.189	0.232	0.345
Equity volatility (10 days)	0.108	0.126	0.16	0.118	0.178	0.115	0.245	0.128
Equity volatility (126 days)	0.17	0.218	0.233	0.195	0.186	0.185	0.212	0.301
Equity volatility (one year, 252 days)	0.15	0.189	0.204	0.206	0.212	0.187	0.198	0.25
Externally financed asset growth	0.01646	0.005579	0.003467	0.015894	0.014159	0.024212	0.014396	0.005204
Promised return on debt	0.032448	0.037703	0.037018	0.039099	0.039176	0.045412	0.043914	0.043556
Rating (UBS group, long term)	Aa2	Aa2	Aa2	Aa2	Aa2	Aaa	Aaa	Aaa
CS								
Total assets (in million CHF)	1433621	1404562	1473113	1255956	1359687	1415174	1376442	1360680
Initial market value of equity (mio. CHF)	80900	74393	77946	90575	101297	100221	86576	76024
Dividend yield on equity	0.0299	0.0263	0.0263	0.0263	0.0263	0.0367	0.0367	0.0367
Book value of liabilities (mio. CHF)	1390991	1365680	1431470	1212370	1315683	1371325	1334477	1317481
Equity volatility (quarter of the year, 63 days)	0.24	0.262	0.201	0.155	0.233	0.184	0.264	0.239
Equity volatility (10 days)	0.109	0.189	0.14	0.092	0.271	0.197	0.26	0.102
Equity volatility (126 days)	0.212	0.249	0.232	0.179	0.195	0.208	0.228	0.256
Equity volatility (one year, 252 days)	0.183	0.212	0.223	0.215	0.214	0.194	0.212	0.233
Externally financed asset growth	0.020816	0.0156	0.00825	0.013813	-0.01915	-0.0047	-0.00581	0.013261
Promised return on debt	0.027851	0.032933	0.031347	0.038239	0.038316	0.041916	0.042177	0.039667
Rating (CS group, long term)	Aa3	Aa3	Aa3	Aa3	Aa2	Aa2	Aa2	Aa2

Table 6: Initial parameter values for UBS and CS

	2008 Q1	**2008 Q2**	**2008 Q3**	**2008 Q4**	**2009 Q1**	**2009 Q2**	**2009 Q3**	**2009 Q4**
UBS								
Total assets (in million CHF)	2231019	2077635	1996719	2015098	1861326	1599873	1476053	1340538
Initial market value of equity (in mio. CHF)	59843	62874	54135	43519	31379	42872	67497	57108
Dividend yield on equity	0	0	0	0	0	0	0	0
Book value of liabilities (in mio. CHF)	2208323	2025342	1941859	1974282	1821620	1558317	1428797	1291905
Equity volatility (quarter of the year, 63 days)	0.67	0.481	1.013	0.987	0.97	0.679	0.405	0.339
Equity volatility (10 days)	0.808	0.547	1.766	0.424	0.876	0.615	0.236	0.229
Equity volatility (126 days)	0.532	0.61	0.786	1.022	0.957	0.835	0.552	0.379
Equity volatility (one year, 252 days)	0.411	0.483	0.691	0.845	0.902	0.933	0.761	0.638
Externally financed asset growth	-0.0180	-0.0188	-0.0259	-0.0187	-0.0147	-0.0159	-0.0321	-0.0451
Promised return on debt	0.0336	0.0322	0.0308	0.0200	0.0126	0.0126	0.0096	0.0091
Rating (UBS group, long term)	Aa1	Aa2	Aa2	Aa2	Aa2	Aa2	Aa2	Aa3
CS								
Total assets (in million CHF)	1207994	1229825	1393599	1170350	1156086	1092904	1064208	1031427
Initial market value of equity (in mio. CHF)	56251	52740	56596	33762	41059	58765	68137	60691
Dividend yield on equity	0.0367	0.0035	0.0035	0.0035	0.0035	0.058	0.058	0.058
Book value of liabilities (in mio. CHF)	1170355	1192977	1354576	1138048	1105428	1042085	1011194	983099
Equity volatility (quarter of the year, 63 days)	0.558	0.284	0.641	1.246	0.868	0.504	0.332	0.337
Equity volatility (10 days)	0.721	0.352	1.129	0.395	0.81	0.61	0.282	0.193
Equity volatility (126 days)	0.428	0.462	0.494	1	1.068	0.699	0.41	0.335
Equity volatility (one year, 252 days)	0.344	0.373	0.474	0.779	0.84	0.869	0.738	0.544
Externally financed asset growth	0.000106	-0.02292	-0.0163	0.003461	-0.00458	-0.00895	-0.03519	-0.01376
Promised return on debt	0.036409	0.03756	0.029335	0.026758	0.017705	0.025134	0.014324	0.013569
Rating (CS group, long term)	Aa2	Aa2	Aa2	Aa2	Aa2	Aa2	Aa2	Aa2

Table 7: Guarantee value (GV) and expected shortfall (confidence interval 95%) in mio CHF for **Credit Suisse** refering to the Benchmark scenario (no jumps, $\mu = \phi = 0$) and cases with different jump intensities μ (per year) and jump sizes ϕ

	Benchmark		$\mu = 0.252,\ \phi = 0.01$		$\mu = 1.008,\ \phi = 0.01$		$\mu = 0.252,\ \phi = 0.05$		$\mu = 1.008,\ \phi = 0.05$	
Time	**GV**	**ES**	**GV**	**ES**	**GV**	**ES**	**GV**	**ES**	**GV**	**ES**
2004 Q1	0	30	10	290	70	1440	2260	42200	7020	84580
Q2	0	0	0	70	50	1000	1960	36390	6530	80620
Q3	0	0	10	260	80	1700	2140	37630	7040	82250
Q4	0	0	0	40	20	490	1740	33680	6330	79370
2005 Q1	0	0	0	0	10	190	1460	28540	6100	77740
Q2	0	0	0	50	30	650	2150	37710	8100	93190
Q3	0	0	0	50	30	590	2190	39210	7920	92860
Q4	0	10	0	70	60	1220	2370	44480	8230	99490
2006 Q1	10	160	40	770	130	2560	3080	58170	9570	117290
Q2	70	1440	110	2280	390	7880	3980	68200	11250	124830
Q3	0	40	30	520	140	2810	3350	58460	10160	116060
Q4	0	0	0	20	20	480	1800	35940	6700	88060
2007 Q1	20	500	50	1060	160	3170	2510	50370	8240	109020
Q2	0	90	20	460	110	2120	2870	54090	9460	112900
Q3	240	4730	330	6590	620	12540	4350	74690	11740	129680
Q4	0	70	10	260	80	1550	2480	41660	9190	99550
2008 Q1	1170	19960	1240	20850	1540	24440	4280	54730	10650	100650
Q2	10	170	30	580	150	3000	2960	42120	9610	93570
Q3	1230	21880	1380	23590	1570	26000	4510	59840	11360	112110
Q4	21340	117830	21800	118710	21770	120060	23010	129740	27490	155660
2009 Q1	2770	36390	2890	37530	3020	38410	5050	59120	10390	96960
Q2	380	7610	440	8790	510	10280	2350	37720	7090	78650
Q3	0	70	10	110	10	260	720	14450	3590	54170
Q4	0	40	0	70	20	360	780	15720	3830	56350

Table 8: Guarantee value (GV) and expected shortfall (confidence interval 95%) in mio CHF for **UBS** refering to the Benchmark scenario (no jumps, $\mu = \phi = 0$) and cases with different jump intensities μ (per year) and jump sizes ϕ

	Benchmark		**$\mu = 0.252$, $\phi = 0.01$**		**$\mu = 1.008$, $\phi = 0.01$**		**$\mu = 0.252$, $\phi = 0.05$**		**$\mu = 1.008$, $\phi = 0.05$**	
Time	**GV**	**ES**	**GV**	**ES**	**GV**	**ES**	**GV**	**ES**	**GV**	**ES**
2004 Q1	0	0	0	0	10	150	1490	29950	7460	109510
Q2	0	0	1	15	10	290	1840	36960	8070	114140
Q3	0	0	0	0	20	400	2050	41250	8610	118110
Q4	0	0	0	9	0	10	1410	28320	7280	106500
2005 Q1	0	0	0	2	0	100	1800	36130	8330	116100
Q2	0	0	0	1	30	700	3240	59730	12560	149160
Q3	0	0	0	8	20	410	2670	52580	11710	149340
Q4	0	0	4	80	40	700	2730	54910	11120	150630
2006 Q1	0	0	2	34	40	740	2970	59590	11680	154870
Q2	188	3781	308	6189	600	12060	6020	112360	16560	199230
Q3	7	135	26	523	160	3150	4490	86310	15230	187020
Q4	9	179	33	665	220	4490	5310	97250	16670	197190
2007 Q1	13	254	98	1978	390	7770	6690	109730	19980	217880
Q2	39	778	159	3193	570	11420	7400	118280	20910	222990
Q3	345	6931	583	11721	1420	28610	9350	132600	24710	232210
Q4	268	5377	417	8370	820	16460	6890	90880	19820	185980
2008 Q1	2033	31380	2299	34022	3190	42970	10210	108630	23980	198470
Q2	224	4504	388	7805	850	16900	6640	83640	18570	168160
Q3	12682	98144	13021	99133	13460	101430	16900	133090	27880	198500
Q4	5173	57373	5424	59229	5920	63910	10680	107350	21980	179310
2009 Q1	1402	24527	1566	26603	2150	33130	6690	81090	17190	152370
Q2	192	3852	241	4850	420	8510	3440	54100	10990	117080
Q3	2	33	6	118	20	390	1190	23820	6060	85090
Q4	0	3	0	10	10	160	1130	22670	5320	74410

Table 9: Guarantee values in mio CHF refering to a historical equity volatility respectively calculated as a rolling 10-, 63-, 126- and 252-days annualized standard deviation of equity price changes

	Guarantee value							
	CS				UBS			
Time	**10 days**	**Benchmark** (63 days)	**0.5 year** (126 days)	**1 year** (252 days)	**10 days**	**Benchmark** (63 days)	**0.5 year** (126 days)	**1 year** (252 days)
2004 1Q	0	0	1	5	0	0	0	0
2Q	0	0	0	1	0	0	0	0
3Q	0	0	0	1	0	0	0	0
4Q	0	0	0	0	0	0	0	0
2005 1Q	0	0	0	0	0	0	0	0
2Q	0	0	0	0	0	0	0	0
3Q	0	0	0	0	0	0	0	0
4Q	0	0	0	0	0	0	0	0
2006 1Q	0	10	1	0	0	0	0	0
2Q	0	70	45	12	0	188	32	2
3Q	0	0	14	14	0	7	41	14
4Q	0	0	1	16	0	9	12	15
2007 1Q	110	20	5	13	10	13	5	38
2Q	10	0	17	11	0	39	33	40
3Q	180	240	79	38	450	345	166	101
4Q	0	0	10	3	0	268	118	16
2008 1Q	3900	1170	307	62	5290	2033	579	107
2Q	60	10	336	87	580	224	1084	259
3Q	22050	1230	251	189	207970	12682	3581	1783
4Q	10	21340	6967	1843	0	5173	6572	1773
2009 1Q	1780	2770	9568	2241	520	1402	1312	708
2Q	1160	380	2485	7324	50	192	1156	2722
3Q	0	0	35	2558	0	2	95	1391
4Q	0	0	1	283	0	0	0	257
Sum	29260	27240	20123	14701	214870	22577	14786	9226
Average	1219	1135	839	613	8953	941	616	384

Table 10: Guarantee value and expected shortfall (confidence interval 95%) in mio CHF refering to a maturity of one year (benchmark case) and five years

	CS				UBS			
	Benchmark scenario		Maturity 5y		Benchmark scenario		Maturity 5y	
Time	**Guarantee value**	**ES**	**Guarantee value**	**ES**	**Guarantee value**	**ES**	**Guarantee value**	**ES**
2004 Q1	0	30	724	15670	0	0	469	10210
Q2	0	0	359	8120	0	0	681	15270
Q3	0	0	413	9250	0	0	499	11090
Q4	0	0	478	10430	0	0	205	4570
2005 Q1	0	0	147	3140	0	0	186	4120
Q2	0	0	139	3050	0	0	585	12600
Q3	0	0	285	6260	0	0	334	7300
Q4	0	10	1798	39330	0	0	2420	52970
2006 Q1	10	160	3782	84200	0	0	4173	93300
Q2	70	1440	6107	117150	188	3781	17205	253850
Q3	0	40	2886	64310	7	135	10642	182850
Q4	0	0	4062	78210	9	179	11886	194340
2007 Q1	20	500	8170	129510	13	254	11931	192450
Q2	0	90	7308	116700	39	778	15788	226760
Q3	240	4730	13928	170500	345	6931	18024	234720
Q4	0	70	657	14570	268	5377	4824	63740
2008 Q1	1170	19960	25129	151250	2033	31380	22784	174750
Q2	10	170	64	1520	224	4504	1087	25120
Q3	1230	21880	20443	138860	12682	98144	160634	482550
Q4	21340	117830	165932	375380	5173	57373	113672	412470
2009 Q1	2770	36390	59403	242530	1402	24527	79938	330460
Q2	380	7610	20017	123520	192	3852	6814	84260
Q3	0	70	587	12550	2	33	30	700
Q4	0	40	520	11030	0	3	0	10

Table 11: Guarantee value (GV) and expected shortfall (confidence interval 95%) in mio CHF refering to a target liability to asset ratio of 90%, 92% (benchmark case) and 98%

	CS						UBS					
	Liability to asset ratio						Liability to asset ratio					
	90%		Benchmark		98%		90%		Benchmark		98%	
Time	**GV**	**ES**	**GV**	**ES**	**GV**	**ES**	**GV**	**ES**	**GV**	**ES**	**GV**	**ES**
2004 1Q	0	0	0	30	550	11030	0	0	0	0	30	620
2Q	0	0	0	0	150	3020	0	0	0	0	40	900
3Q	0	0	0	0	370	7360	0	0	0	0	40	710
4Q	0	0	0	0	130	2640	0	0	0	0	0	70
2005 1Q	0	0	0	0	10	240	0	0	0	0	0	30
2Q	0	0	0	0	70	1340	0	0	0	0	80	1560
3Q	0	0	0	0	80	1580	0	0	0	0	10	210
4Q	0	0	0	10	340	6820	0	0	0	0	260	5230
2006 1Q	0	10	10	160	1060	21300	0	0	0	0	280	5640
2Q	10	270	70	1440	2700	47360	38	766	188	3781	4810	83610
3Q	0	0	0	40	940	18860	2	49	7	135	1600	32050
4Q	0	0	0	0	200	4050	0	2	9	179	2130	42590
2007 1Q	10	110	20	500	1430	28790	1	17	13	254	3080	56530
2Q	0	10	0	90	1020	20480	3	57	39	778	4480	73650
3Q	80	1560	240	4730	4460	64580	60	1214	345	6931	9480	109150
4Q	0	10	0	70	760	12180	71	1425	268	5377	6090	48400
2008 1Q	600	11970	1170	19960	6000	43460	856	17077	2033	31380	14760	74220
2Q	0	20	10	170	1250	14340	58	1169	224	4504	5930	41900
3Q	660	13260	1230	21880	6510	49560	9306	86028	12682	98144	28910	134700
4Q	18570	112490	21340	117830	33340	139500	3072	44276	5173	57373	17670	94790
2009 1Q	1920	29930	2770	36390	8180	58140	697	14011	1402	24527	9230	59530
2Q	170	3490	380	7610	2910	30040	57	1147	192	3852	2680	29930
3Q	0	0	0	70	210	4140	0	4	2	33	240	4870
4Q	0	10	0	40	190	3720	0	0	0	3	50	1050

Table 12: Guarantee value and expected shortfall (confidence interval 95%) in mio CHF refering to quarterly audits (benchmark case) and additional daily audits during stressed times, i.e., asset to liability ratio falls to 101%

	CS				**UBS**			
	Benchmark scenario		**Adjusted audits**		**Benchmark scenario**		**Adjusted audits**	
Time	**Guarantee value**	**ES**	**Guarantee value**	**ES**	**Guarantee value**	**ES**	**Guarantee value**	**ES**
2004 Q1	0	30	0.3	6.6	0	0	0	0
Q2	0	0	0	0	0	0	0	0
Q3	0	0	0	0	0	0	0	0
Q4	0	0	0	0	0	0	0	0
2005 Q1	0	0	0	0	0	0	0	0
Q2	0	0	0	0	0	0	0	0
Q3	0	0	0	0	0	0	0	0
Q4	0	10	0	0	0	0	0	0
2006 Q1	10	160	2.4	48.3	0	0	0	0
Q2	70	1440	21.7	436.4	188	3781	54	1084
Q3	0	40	0.9	17.3	7	135	2	50
Q4	0	0	0	0	9	179	4	75
2007 Q1	20	500	7.6	151.8	13	254	5	101
Q2	0	90	1.1	21.3	39	778	10	206
Q3	240	4730	66.6	1337.7	345	6931	83	1662
Q4	0	70	1.5	29.8	268	5377	85	1665
2008 Q1	1170	19960	272.8	2752.5	2033	31380	793	4589
Q2	10	170	4.7	95	224	4504	272	2592
Q3	1230	21880	334.6	3268	12682	98144	2447	9285
Q4	21340	117830	2485	2496.7	5173	57373	1318	6549
2009 Q1	2770	36390	612.8	4277	1402	24527	679	4237
Q2	380	7610	84.8	1515.1	192	3852	86	1559
Q3	0	70	1.3	26.1	2	33	2	32
Q4	0	40	0.8	16.2	0	3	0	3

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To be ‘too big to fail’ - distorted liability insurance premiums across U.S. banks

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Abstract

In this paper I address several questions in the context of estimating the value of the implicit guarantee of financial institutions which are considered as ‘too big to fail’ (TBTF). First, I investigate more closely the often assumed refinancing advantage of TBTF institutions. Comparing quarterly interest expenses across U.S. banks during 2004-2009, I find evidence that TBTF banks were able to refinance under more favorable conditions than Non-TBTF institutions during 2008-2009. Second, I revisit an options-based approach for computing the liability insurance premium. Some input parameters as asset volatility are determined by the market perception about risk and future returns. Therefore, the estimated premiums should also reflect the TBTF status of a bank and therefore distort the level of the insurance premium. I analyze the magnitude and dynamic of emerging differences in insurance premiums relative to total assets between TBTF and Non-TBTF banks. Third, I study the absolute level of these premiums and the impact of higher capital requirements.

1 Introduction

Authorities all over the world implemented different measures including liquidity provision or stimulus packages to stabilize the financial system and to mitigate the decline in real economic activity during the financial crisis. Beside these general measures, there were bailouts necessitated by the systemic relevance of large so called 'too big to fail' (TBTF) banks. These interventions were not justified by a contract but by the pivotal role of these institutions for the financial industry and ultimately the economy as a whole and is often called implicit guarantee. There exist two competing approaches for the valuation of the implicit guarantee. The cash-flow approach estimates the refinancing advantage of a systemic relevant bank in comparison to others. In contrast, the contingent-claim approach determines the fair premium for insuring the liability side of a bank. Therefore, the implicit guarantee is interpreted as exclusive liability insurance.

This paper studies both approaches for the financial sector in the United States (U.S.) from 2004 to 2009. First, I investigate differences in refinancing costs of TBTF and Non-TBTF banks using annualized quarterly interest expenses on debt as dependent variable. After controlling for a range of variables which influence the refinancing costs of a firm, I find evidence that TBTF firms could fund their operations under more favorable conditions than their competitors during the last two years, the time the U.S. government implemented an official TBTF policy. In the second part of the paper, I revisit the contingent-claim approach which is based on the work of Black and Scholes (1973) and Merton (1974) on debt pricing. The estimation of the liability insurance premium – used as a proxy for the implicit guarantee value – is based on balance sheet data as total assets or liabilities and market data as market capitalization and equity volatility. Latter quantities are determined by the market perception about risk and future returns, therefore are also influenced by the implicit state guarantee. I examine more closely differences in asset volatility between Non-TBTF and TBTF banks and study the impact of the described endogeneity effect on the level of liability insurance premiums across banks. I can show that premiums relative to total assets differ substantially between systemic relevant and other banks. If the gap is attributable to the TBTF policy of the U.S. government, one can argue that the policy was successful in the sense that the guarantee value was relatively lower for TBTF institutions than for the rest of the studied financial sector. In the last part of my work, the evolution of absolute premiums accumulated for TBTF institutions is studied. The analysis of higher capital requirements (target liability-to-asset ratio of 70%) shows that the average amount of liability insurance premiums can be reduced by around 40%, i.e., potential bailouts should be much cheaper for tax payers.

The paper contributes to an important topic and a large literature (see Section 2) in several ways. Baker and McArthur (2009) find in the U.S. a positive spread between the average costs of funds of the two groups indicating that counterparties (debtholders) seem to be able to distinguish TBTF and Non-TBTF institutions and therefore require a lower risk premium. They state, but do not verify, that if this gap is attributable to the government guarantee it implies a taxpayer subsidy for the TBTF banks. I use a different data set, conduct a rigorous analysis and find consistent results. For the second approach, I closely follow Lucas and McDonald (2006, 2009), who extend and adapt the work of Merton (1974, 1977) for detecting the risk inherent in government-sponsored enterprises (GSE). In contrast to former authors, I am interested in the impact of the described endogeneity on the liability insurance premiums. For completeness I discuss the absolute premium development, also in the light of proposed regulatory changes, at the end.

The stated endogeneity effect can be justified by two channels: market discipline and charter value (see Cordella and Yeyati (2003)). The interest rate a bank pays for its deposits or debt in general should reflect the possibility of losses on debt in case of a bankruptcy (risk premium). By removing these possible losses by a total debt insurance or preventing the default itself, bank's creditors have a lower incentive to monitor the risk policy and therefore do not demand adequate risk premiums (Flannery and Sorescu (1996)). In contrast to an explicit guarantee, I call the guarantee implicit if there does not exist a contract between bank and guarantor although there are reasons to assume that a guarantee exists. The intervention is uncertain and the implementation is not specified. Therefore, it is unlikely and also not observed in reality that the whole risk premium can be avoided, i.e., TBTF banks would pay only a risk-free rate. However, there is evidence (see Section 2 and Subsection 5.1) that TBTF institutions pay a reduced interest rate compared to Non-TBTF banks and consequently the initial circumstances for the two channels are given. On the one hand, shareholders are probably encouraged to increase the risk profile of the company, because cost of funds are not totally tied to the riskiness and often also shareholders are bailed out. The non-specification which goes along with the missing contractual framework makes it difficult to infer definite consequences, but as we have seen the free implicit state guarantee induces market discipline problems with respect to shareholders and debtholders. On the other hand, since the guarantee is not paid by the shareholders this should directly increase profits. This makes the firm more valuable because as long as the institution exhibits the TBTF status it is able to generate a dividend stream of lower refinancing costs. In a reverse conclusion, this channel induces decreased risk-taking for protected banks (and higher risk-taking for competitors as Gropp, Hakenes, and Schnabel (2010) show), because in the default case without bailout – which is possible with a certain probability since the implicit guarantee is not certain and specified – the TBTF institution loses future rents from lower refinancing costs and therefore has an incentive to protect the charter value. The resulting direction of these two effects is not clear. In Subsection 3.2, I revisit Lucas and McDonald (2009) and describe the implications for asset volatility. Later in the empirical part, we can observe differences in asset volatility but also in the relative guarantee premiums between Non-TBTF and TBTF banks.

This paper is organized as follows. I give a short literature review in Section 2. Section 3 provides a model description, presents the implications of the TBTF status for the asset volatility and discusses differences of both approaches. Section 4 gives an overview of the data and the parameter specification for the simulation. The results are analyzed in Section 5. Section 6 concludes.

2 Literature review

I present a selection of the comprehensive literature review of Haefeli and Jüttner (2010). In particular the documented empirical evidence of market responses to the TBTF status of banks and interrelated market discipline consequences are relevant. The different approaches for determining the size of the guarantee are presented at the end.

The seminal papers of O'Hara and Shaw (1990) and Flannery and Sorescu (1996) study different market effects in connection with the financial crisis involved the Continental Illinois Corporation in July 1984. Former authors report an average 1.3% abnormal return to common equity of TBTF banks. This result indicates that the market believed that government policy would protect bank owners from at least some types of financial difficulties. In contrast, Flannery and Sorescu (1996) ask whether banks' debtholders were rationally pricing bank-specific risks during 1983-1991. They find that when government's willingness to insure bank subordinated debtholders declined over time, debenture yields reflected the specific risk of banks as leverage and asset quality. Morgan and Stiroh (2005) focus on the relationship between TBTF bond spreads and risk relative to other banks. Their findings suggest that also the Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991 - which limits regulators' discretion to support distressed relevant banks[1] - did not entirely shaken investors' beliefs in TBTF which put the results of Flannery and Sorescu (1996) a bit into perspective. Rime (2005) uses bank ratings to test the presence of TBTF expectations. Völz and Wedow (2009) examine the credit default swap (CDS) market, i.e., the authors quantify the potential distortion due to TBTF expectation on CDS prices. Spreads tend to be lower for banks with a larger size relative to home country's gross domestic product. A more recent study of Peristiani, Morgan, and Savino (2010) detects bank investors' and counterparties' ability to judge bank solvency during the current crisis. They find that the market was able to distinguish between banks with a capital gap and adequately capitalized banks before the results of the Supervisory Capital Assessment Program were released.

For the determination of the approximate magnitude of this implicit guarantee value, I identify mainly two strains of literature: *contingent-claim* and *cash-flow* analysis. In the latter valuation method, traded securities with and without guarantees are compared and the price difference between these securities is interpreted as the implied value. Passmore (2005) calculates the implicit guarantee value to Fannie Mae & Freddie Mac (F&F) (shareholders and homeowners)

[1]For details about the FDICIA especially in the context of the TBTF discussion see the review of Wall (2010) and references therein. This article was originally published in 1993 but due to the current crisis and discussion reprinted in 2010.

using a cash-flow approach. He estimates the gross subsidies from the borrowing advantage by comparing yields on financial corporate debt and debt of a government-sponsored enterprise. Baker and McArthur (2009) investigate the spread between the average cost of funds for small banks and the cost of funds for systemic relevant institutions with assets in excess of $100 bn and find that the gap widened in the period from the fourth quarter of 2008 through the second quarter of 2009, after the government bailouts had largely established 'too big to fail' as official policy.[2] This gap implies a government subsidy of $34 bn a year for this set of banks. The evaluation of loan insurance using contingent-claim models is based on the initial work of Merton (1977) and Merton (1978) which follows the research on corporate debt pricing (Black and Scholes (1973) and Merton (1974)) by applying option pricing theory. Merton (1977) derives an options-based formula to evaluate the cost on the guarantor for issuing a guarantee of bank deposits. Merton (1978) extends the earlier framework taking into account explicitly surveillance costs and random auditing times. This approach is for instance applied by Lucas and McDonald (2006) on F&F for the year 2005, where the results compared to Passmore (2005) are much lower. Haefeli and Jüttner (2010) focus on the Swiss situation and compute the guarantee value for Credit Suisse (CS) and UBS quarterly in a dynamic setup from 2004 until 2009. They determine the erratic evolution of the guarantee value through the crisis.

3 Model

As already stated, my aim is to back out possible distortions in liability insurance premiums induced by the TBTF status of financial institutions where premiums are calculated using a Merton based approach. In this section I revisit the cases of a single- and multi-period guarantee. Associated theoretical implications for model input variables are derived. Moreover, I discuss some issues related to the assumptions and interpretation of the different approaches. Later I present the simulation approach and the choice of parameters for estimating liability insurance premiums. I follow in parts closely Lucas and McDonald (2006) and Lucas and McDonald (2009).

For clarification, in the contingent-claim approach the bailout is naturally related to an exclusive liability insurance and not a combined one with 'not to withdraw the bank's charter', i.e., if the bank defaults the promised debt is repaid and the bank is liquidated for sure. Therefore, the observed survival of failed banks through the recent crisis, implicitly assuming that the bailout is a combination of deposit insurance and not closing the bank (withdraw the charter) is not incorporated. By construction, the intervention is not uncertain and its design is specified.

3.1 Single period guarantee

Analog to Lucas and McDonald (2009) I distinguish two groups of debt issuing banks: insured and uninsured institutions, indexed by $\{I, U\}$, where all banks have the same physical assets

[2]See Table 4: the measures of the Federal Reserve in March 2008, in particular financing support of JPMorgan Chase & Co.'s acquisition of The Bear Stearns Companies Inc. can be interpreted as one of the first steps to establish a policy of supporting systemic relevant banks.

and risk profile. The status 'insured' or 'uninsured' is fixed at the beginning of the considered time period and does not change through time. I discuss the case of a single period explicit liability insurance, i.e., I calculate the implicit guarantee value as if it had been explicit. The debt contract has length T. Bank's assets evolve stochastically over time and at time T the bank is capable to repay the promised debt repayment D_T, i.e., $A_T > D_T$ or it defaults. At T each bank is liquidated: in case of a default shareholders lose everything (otherwise they have $A_T - D_T$), debtholders of uninsured banks receive the residual asset value after liquidation, debtholders of insured institutions get the promised debt repayment, i.e., the guarantor has to pay the difference between residual asset value and promised debt payment. Since asset value specifications are equal across banks, the equity value is given by

$$E_0 = e^{-r_f T}\mathbf{E}_0[\max\{A_T - D_T, 0\}], \tag{1}$$

where r_f denotes the riskfree rate and $\mathbf{E}_0[\cdot]$ is the expected value with filtration $\mathcal{F}_0$ under the risk-neutral measure $\mathbb{Q}$. The value of insured debt at time t is then simply the discounted value of the promised repayment:[3]

$$D_0^I = e^{-r_f T} D_T \quad \text{and}$$

the value for uninsured debt is given by the discounted expected value of the repayment:

$$D_0^U = e^{-r_f T}\mathbf{E}_0[\min\{A_T, D_T\}]. \tag{2}$$

The difference between these values is the guarantee value, here at time 0:

$$G_0 = D_0^I - D_0^U = e^{-r_f T}\,\mathbf{E}_0[\max\{D_T - A_T, 0\}]. \tag{3}$$

If I assume that the guarantor is non-defaultable and the guarantee is announced before debt is issued, debtholders do not ask for any risk premium. In contrast, financial institutions which do not exhibit a deposit insurance have higher refinancing costs of the same magnitude. This value corresponds to the expected default payments and therefore should be compensated by the risk premium.

With this determination of the guarantee value I obtain for I the asset value at time 0:

$$A_0^I = E_0 + D_0^I = E_0 + D_0^U + G_0,$$

where G_0 can be interpreted as a dividend for shareholders or a lower initial investment from equity holders, because they are not paying the premium to the guarantor.[4] For a solution of equation (1) or (2) there exist a vast literature in the area of corporate bond pricing (see for in-

[3]For the present value at time t, write and calculate: $D_t = e^{-r_f(T-t)}D_T$.

[4]Note the assumption that the guarantee value accrues completely to shareholders is debatable. In the case of F&F Passmore (2005) finds that these institutions partly transmit their refinancing benefits on to credit users which is not so surprising because they were founded in order to support households providing better conditions for mortgages.

stance Longstaff and Schwartz (1995), Leland and Toft (1996) or Collin-Dufresne and Goldstein (2001)). For convenience, the structural framework of Merton (1974) is given in Appendix A.

3.2 Repeated debt guarantee

In the second subsection I discuss the differences between evaluating liability insurances of insured and uninsured institutions which arise by considering more periods. Lucas and McDonald (2009) develop a theoretical framework and derive implications for asset evolution and volatility levels due to the impact of the TBTF status on market variables. The technical details can be found in Appendix B. Intuitively, in the multiperiod case banks have as long as they are not defaulted at the beginning of each period the possibility to issue debt. Uninsured institutions pay each period the appropriate risk premium on debt and declare bankruptcy as soon as they are not able to pay back the outstanding liabilities at the end of the period, i.e., $D_{m-1}(T) > A_m(0)$.[5] In contrast, insured institutions generate by issuing periodically guaranteed debt for lower refinancing costs a dividend stream as long they are in business. As before, the bailout is restricted to repay outstanding liabilities once. Therefore also at debt reset dates where current assets are not sufficient for repaying the outstanding debt amount, shareholders do not declare bankruptcy, i.e., they pay off the outstanding liabilities by themselves, if the current value of assets and the expected guarantee value stream is higher than the current liabilities and expected future payments of outstanding debt amounts. Therefore the declaration of a default is not just dependent on the current level of operating assets and debt but also on the expectations regarding future rewards and costs (so called market assets). The continuity condition for an insured institution at each debt reset date mT is given by

$$A_m(0)(1+\Gamma-H) > D_{m-1}(T), \tag{4}$$

where Γ is the value of the dividend stream and H the cost component. With this insight Lucas and McDonald (2009) define market assets on a debt reset date as

$$A_m^*(0) = A_m(0)(1+\Gamma-H) \tag{5}$$

and the market asset volatility is then proportional to the asset volatility of operating assets, i.e.,

$$\sigma_{A^*} = \sigma_A(1+\Gamma-H). \tag{6}$$

Consequently, it is possible that we observe today different (lower or higher) market asset levels or volatilities for insured or uninsured financial institutions with the same operating assets and risk profile. These variables among others are used for estimating the liability insurance premium or corresponding risk premium and therefore distorted results are obtained. In contrast to the

[5] Notation: $X_m(t)$ is the value of X at time $mT+t$, where $m \in \mathbb{N}_0$. Therefore, $D_{m-1}(T)$ denotes the promised payment at time $(m-1)T+T$, the debt amount which was settled at time $(m-1)T$. Each period has length T.

presented approach, Cordella and Yeyati (2003) or Ennis and Malek (2005) use a 'constructive ambiguity' bailout, i.e., a bailout is not certain but occurs with a certain probability.[6] Moreover, former authors include the possibility of a 'rebirth' since a bailout is here 'not to withdraw' the bank license and the payment of the outstanding liabilities in the case when the bank is not able and not willing via recapitalization to meet its liabilities. The potential bailout generates also here two opposite effects: a market discipline problem and the so called value effect. On the one hand, the probability of surviving depends less on the bank's choice of risk and more on the supervisory authority's action, therefore, shareholders have an incentive to choose riskier asset portfolios for maximizing expected profits, which of course, also increases the default risk. On the other hand, governmental guarantees naturally increase the survival probability and future rents due to lower refinancing costs, thus raising the charter value in the case of a default, which, in turn, generates the incentive to protect it by reducing the asset portfolio risk.

3.3 Discussion

First, there is controversy in the literature why the approaches from Passmore (2005) and Lucas and McDonald (2006) lead to strongly different results for the implicit guarantee value (see for instance Lehnert and Passmore (2006) or Lucas and McDonald (2009)). It is stated that both 'techniques should produce similar results if the difference in yields between GSE debt and private debt mainly reflects the implicit government guarantee'. But why? The cash-flow approach characterizes the implicit guarantee as subsidy from the *refinancing advantage* (difference in the risk premium), whereas the contingent-claim approach calculates a value which corresponds to an explicit guarantee, i.e., if a GSE or TBTF institution defaults the government will bail out all debtholders. Therefore, this value equates to the *total risk premium* and not only the difference. In my opinion, the difference in explicit liability insurance premiums (which is not done in the literature) corresponds in a theoretically correct way to the refinancing advantage (spread in market risk premiums). However, it is conventional wisdom that some of the structural credit risk models are not capable in producing spreads as high as observed in the corporate bond market (see Eom, Helwege, and Huang (2004)). In Lucas and McDonald (2006) the estimated values (total risk premium) from the options approach are smaller than the calculated spread difference. Note that the estimations were done in a static setup for the unstressed (low volatility) year 2005.

Second, it is often criticized that with the contingent-claim estimation approach a 'rebirth' is not possible because the option can only be executed once. Already explained in the subsection before, one possible extension in the Merton framework is the incorporation of repeated debt guarantees and therefore anticipating additional aspects of an implicit guarantee. But also here the bailout is restricted to repay outstanding liabilities once. To my knowledge there does not exist an approach which incorporates the possibility of a 'rebirth' in the estimation of the implicit guarantee value. Independent of the different methods - cash-flow or options based - researchers

[6] They do not estimate the value of the implicit guarantee but discuss emerging moral hazard or incentive problems.

focus on the insurance of deposits or more general of debtholders in case of a default. I agree that the fact that TBTF banks do not disappear is also an essential point in this discussion but one has also take into account that the status of a bank (TBTF or not) or the governmental policy may change through time and therefore also the bailout probability. In general, also the assumption of allowing to keep the bank's charter can be questioned.

3.4 Simulation approach and parameter specification

In Subsection 3.1 I presented the well-known idea to evaluate the liability insurance as a European put option on the underlying assets with maturity date of the debt and with the future book value of debt as the strike price. Up to now, I did not specify the stochastic nature of the underlying processes which is necessary for the implementation. Lucas and McDonald (2006) propose a model where they take into account that financial institutions are able to leverage or deleverage, default before the maturity of debt, are supervised by a regulator and are also exposed to stressed market environments with high volatilities. The complexity of the model necessitates the computation of the put option price via Monte Carlo simulation. The asset paths evolve according to the risk neutral discrete time formula with log-normally distributed returns:

$$A_{t+h} = A_t \exp\left((r_f + g_t - \delta \frac{E_0}{A_0} - \frac{\sigma_A^2}{2})h + \sigma_A \epsilon \sqrt{h}\right) \tag{7}$$

where h is the time step, A is the asset and E denotes equity. Subscripts represent time. r_f is the risk-free rate, g_t is the externally financed asset growth, δ is the dividend yield on equity, $\delta \frac{E_0}{A_0}$ is the dividend yield on assets, σ_A is the volatility of the assets and $\epsilon \sim \mathcal{N}(0,1)$ is standard normally distributed. Since the initial market value A_0 and volatility σ_A of the assets are not directly observable, the following equations which are based on Merton's framework (see the details in Appendix A) are solved simultaneously for A_0 and σ_A (see for instance Ronn and Verma (1986) or Bohn and Crosbie (2003)):

$$E_0 = A_0 e^{-qT} N(d_1) - L_0 e^{-r_f T} N(d_2) + A_0(1 - e^{-qT}), \tag{8}$$

$$\sigma_A = \sigma_E \frac{E_0}{A_0} \left(N(d_1)e^{-qT} + (1 - e^{-qT})\right)^{-1}, \tag{9}$$

$$d_1 = (\log(A_0/L_0) + (r_f - q + \frac{\sigma_A^2}{2})T)/(\sigma_A \sqrt{T}),$$

$$d_2 = d_1 - \sigma_A \sqrt{T},$$

where T is the maturity of liabilities, L_0 is the strike price (initial book value of liabilities), σ_E the equity volatility and $q = \delta \frac{E_0}{A_0}$ is the payout rate of assets.[7]
Moreover, the evolution of the book value of liabilities L is assumed to adjust towards a target liability to asset ratio λ^*:

$$L_{t+h} = L_t e^{(r^d + \gamma g_t)h} + \mathbb{I}_t \alpha_t h(\lambda^* - L_t e^{r_d h}/A_t)A_t \tag{10}$$

[7]The last term $A_0(1 - e^{-qT}) = \int_0^T q A_0 e^{-qt} dt$ in the first equation represents the accumulated dividend payments.

where α_t denotes the annual rate of adjustment, λ^* is the target liability to asset ratio, $\mathbb{I}_t$ is an indicator variable that equals 1 in a period where liabilities are adjusted and 0 otherwise, r^d is the growth rate of liabilities to cover promised coupons and γ is the fraction of externally financed growth supported by debt.

The simulation of the asset and liability path (equations (7) and (10)) requires the calibration of the introduced parameters. The asset growth rate is determined by the logarithm of the difference in total assets.[8] Therefore, the asset growth rate is adjusted dynamically at every starting point based on the average growth rate of the last year taking into account changing market conditions. For the dividend yield q, I use the respective quarterly dividend and annualize it. Moreover, I employ the historical equity volatility, which is calculated as a rolling 60-day annualized standard deviation of equity price changes. Later, I also show some robustness results with respect to other volatility specifications. Time to maturity T is set to one year, since I am interested to determine the implicit guarantee value for one year. I assume that debt is homogenous with a maturity of one year. This is a strong assumption recognizing that the debt structure of these banks is diversified with all kinds of maturities and seniorities. For the liability path (see equation (10)) I also need information about the growth rate of liabilities to cover promised coupons. I determine r^d by the fraction of annualized interest rate expenses over outstanding liabilities of the last quarter (see Subsection 4.2). I fix some parameter values for all banks (see Table 1), which are quite similar to Lucas and McDonald (2006). The target

Table 1: Common parameter values for all banks and for all starting times

Name	**Value**
Target liability to asset ratio	0.92
Debt proportion of external financing	1
Adjustment of liabilities to higher target	0.8
Adjustment of liabilities to lower target	0.4
Frequency of updating debt	252
Default trigger	1
Frequency of checking bankruptcy trigger per year	4
Time steps per year	252
Time to maturity	1y
Number of Monte Carlo simulations	40000

liability to asset ratio is set according to the Basel II framework to 92%, where I am aware of the fact that Basel incorporates, e.g., risk weighted assets or stressed recovery values to determine the capital requirements. It is assumed that asset growth is completely financed externally by debt. Liabilities adjust gradually and asymmetrically.[9] The 80% per year adjustment up versus 40% per year adjustment down reflects the difficulty for a financial institution to deleverage in

[8]In formulas: $\log\left(\frac{\text{Total Asset}_t}{\text{Total Asset}_{t-1}}\right)$ averaged over the last two quarters.

[9]In equation (10) I set $\mathbb{I}_t \equiv 1$. Hence, the liabilities are adjusted in each time step which is typically each day.

times when asset values are declining.[10] Since I obtain the equity volatility based on daily data, I also run the simulation with 252 time steps per year. To include stressed markets, Lucas and McDonald (2006) rise volatilities by four times to its normal level when assets fall to 101% of liabilities, taking into account increasing volatilities during these times. As in Haefeli and Jüttner (2010), I assume this procedure over the period of moderate market conditions (2004-2007). In turbulent times (2008-2009), I adjust this approach by halving the volatility when assets increase to 110% of liabilities. The identification of financially stressed or unstressed times takes place in every time step of the simulation. For the default trigger[11], based on the asset value relative to book liabilities, I take a value of one. Following Merton (1978), I allow for audits at some pre-specified dates (four times per year) which examine if the asset liability ratio falls below the default trigger. If this case occurs, asset and liability processes are stopped, i.e., the values are held constant and multiplied with the appropriate discount rate until maturity. At maturity, the put option payoffs $\max(L_T - A_T, 0)$ of all paths are collected and the put price is computed as the expected discounted payoff.

4 Data and parameters

In this section, I describe the dataset I use for a closer examination of the refinancing advantage of TBTF banks and for the calculation of the single period insurance premiums across U.S. banks. There exist firms in the sample for which possibly single values of input parameters are not reported and therefore results of single quarters (for instance, interest expenses or guarantee value) cannot be determined. However, I do not remove these firms in total but consider all residual available quarters. Therefore, the cross-sectional sample size is varying across time and object I investigate.

4.1 Company selection and time horizon

Since I need on the one hand balance sheet information as total assets or liabilities and on the other hand daily stock prices to determine the historical volatility I use data from the Merged Database Center for Research in Security Prices (CRSP)/Compustat. I collect data for all firms with Standard Industrial Classification (SIC) codes 60, 61, and 62. Firms with these SIC codes are defined as commercial banks, non-depository credit institutions, and investment banks, respectively (see Table 5). Henceforth, I refer to the set of all banks collectively as financial firms and, for the sake of brevity, rename the second category as 'credit institutions'.

[10]The important point here is that the specification of the liability path allows financial institutions to increase or decrease leverage. In particular, as pointed out in Bohn and Crosbie (2003), financial institutions tend to deleverage as they approach to default in contrast to industrial firms where often liabilities are increased near default.

[11]Bohn and Crosbie (2003) do not find evidence for a default when the asset value of general firms (no financials) reach the book value of liabilities; many continue to operate and service their debts also above this point. They state that the actual default point lies between total and short-term liabilities. Therefore, I impose a quite conservative assumption.

I have to adjust the dataset with respect to several dimensions. First, only firms are considered which report their results quarterly for the time period 2004-2009. Banks are allowed to subsequently default (to preclude a potential survivorship bias), be founded, be taken over by or merged with another company during the period. Second, I exclude data for all financial firms that are not incorporated in the U.S., because these firms will be influenced by regulations applicable in the country of incorporation. However, for the purpose of our study a uniform regulatory regime is required to ensure the comparability across all banks. In total, I have data of 916 financial firms with the majority belonging to the first category (779 banks). This number compares to 8000 FDIC-insured banks in the U.S. at the end of 2009.[12]

Analog to Baker and McArthur (2009) or Chesney, Stromberg, and Wagner (2010), I define a group of TBTF institutions (see Table 6) that consists of (a) those companies that had to participate at the Supervisory Capital Assessment Program (SCAP), (b) those financial institutions that belong to the group of so called government sponsored enterprises (SIC code 6111) and (c) some companies (Wachovia, Washington Mutual, Golden West Financial, Countrywide Financial, Lehman Brothers, Merrill Lynch) which belong or belonged to the biggest banks in the U.S. measured by market capitalization or total assets and were considered by many participants as TBTF.[13] In total, this yields 30 financial institutions. Note, I exclude GMAC and Metlife though these firms participated at the SCAP program, but the former company is not publicly traded and the latter firm is an insurance company. Table 6 gives us an overview of the set of financial institutions I consider as TBTF and study in this work.

4.2 Summary statistics

Table 7 gives us a first impression and overview of the underlying data. Across all banks and all quarters from 2004-2009 there are around 16200 observations where 86% belong to the first group of commercial banks. Therefore, I concentrate my analysis very often on this group. The total asset distribution is highly skewed for all subclasses. On the level of all banks the mean is around 19 times higher than the median. We observe a 10th quantile of \$300 million versus a 90th quantile of \$14 billion. Between the different groups of financial firms the distributional properties of leverage ratios differs a lot. Obviously, the leverage ratios of commercial banks are by far less dispersed than of credit institutions and investment banks. This is also reflected in the statistical measures for the interest expenses.

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[12] FDIC Bank Statistics and Data are available at `http://www.fdic.gov/bank/statistical/`.

[13] It is possible that market participants suppose that a bank is systemic relevant and has an implicit guarantee before default. But the guarantor may decide to let the bank go bankrupt in default. In this case, the implicit guarantee exists until default in the terminology. For instance, Lehman Brothers was certainly assumed to be TBTF by many market participants and ex-post it is questionable whether the supervisory authorities would decide in the same way and follow the 'constructive ambiguity' policy as they did keeping in mind the calamitous and destructive effects on the financial system which accompanied the bankruptcy of Lehman Brothers.
A more detailed and conceptual introduction of this term can be found in Haefeli and Jüttner (2010). Especially, if we look on the events related to these institutions the assumption can be justified. A detailed list of events during the considered time horizon can be found in the Appendix, Table 4.

Total assets Table 8 presents the average total assets of Non-TBTF and TBTF banks in each considered subset (commercial banks, depository institutions and investment banks) as a fraction of total assets of all financial firms in the sample in each quarter for the whole period. First, note that TBTF institutions hold about 80% of total assets during the years. Second, the total assets are unequally distributed across the different finance industry sectors. In particular on the level of Non-TBTF companies the concentration of total assets hold by credit institutions (1.41%) and investment banks (2.49%) is negligible. For TBTF banks the situation is different: we observe a varying proportion of around 16-26% of total assets and corresponding number of observations from credit institutions. Note, that big GSEs, e.g., Fannie Mae or Freddie Mac, belong to this group.[14] TBTF commercial banks increase their fraction of total assets from around 40% at the beginning of the considered period up to 46% at the end of 2009. This increase can be explained by the acquisitions of Countrywide and Merrill Lynch by the Bank of America in the years 2008 and 2009.

Market capitalization Table 9 provides the average market capitalization (market cap) of Non-TBTF and TBTF banks in each considered subset (commercial banks, depository institutions and investment banks) as a fraction of market cap of all financial firms in the sample at the end of each quarter for the whole time period. Naturally, the market valuation of equity is more volatile than the book value of total assets I considered before. The market cap fraction of TBTF financial firms range from around 71% (2007 2Q) to 55% (2009 1Q). Especially, credit institutions loose around 70% of their fraction. The valuation of Non-TBTF investment banks ranges from 4% to 15% (2009 1Q) which is in general a much higher fraction than for the total asset case. The countercyclicality indicates that this class compared to the financial firms in the other subsets performed better during the crisis.

Leverage ratio Figure 6 depicts the development of accounting and market leverage ratios of Non-TBTF and TBTF banks across commercial banks, credit institutions, investment banks and the aggregate set. The accounting leverage ratio is defined as the quotient of book value of total liabilities and book value of total assets, where for the market leverage ratio the denominator is replaced by the sum of book value of total liabilities and market value of equity. First, we observe on the level of all financial firms for both leverage measures a relative stable spread of approximately 5% between TBTF and Non-TBTF banks. In market terms, the leverage in the financial sector increased during the considered time period by approximately 9%. At the end of 2009 (Non-)TBTF banks had a ratio of (86%) 91% probably induced by declining equity prices. Second, in contrast to all other diagrams the market leverage ratio of Non-TBTF and TBTF commercial banks (the group with by far most observations) evolves both on level and

[14]In particular, between 1Q-2Q 2004 we observe large jumps in this proportion but also in the number of observations, also 2Q 2005-4Q 2006. As already noted, for some quarters certain numbers are not available in the used database Compustat/CRSP. For instance, total assets for Fannie Mae were not reported for the some quarters of the years 2004 and 2006.

direction very similar. Both measures for credit institutions and investment banks exhibit a very pronounced spread (up to 50%). Third, in accounting terms the relation between Non-TBTF and TBTF commercial banks reverses at the beginning of 2009.

Interest expenses on debt Table 10 reports the average annualized interest expenses across the different subsets of financial firms. Banks announce interest and related expenses in their financial statements quarterly. To obtain annualized and interpretable quantities, I quadruple the expenses and express them as fractions of total liabilities. It is clear that many features of the complicated debt structure from financial institutions cannot be captured. Banks issue debt at intermediate dates, with different seniorities and maturities, in the form of bonds, deposits from banks with or without collateral or from individuals. Therefore, the reported interest rates represent the aggregated result of all these financing (and investment) decisions probably of the last years and not only the last quarter.[15] However, I use this measure for a first indication regarding the level and development of the interest rate spread between Non-TBTF and TBTF firms in each respective subset. First, we observe a permanent positive spread for credit institutions. On average Non-TBTF institutions in this group have to pay around 2% p.a. more on debt than TBTF firms during the years 2004-2009. This huge difference can be explained by the fact that the TBTF firms in this group are mainly GSEs, firms which were founded by the government and though not directly guaranteed (at least up to September 2008) have been beneficiaries of the proximity to the government.[16] Recalling the results for credit institutions from the former paragraph about market leverage differences (Figure 6), this positive spread is even more remarkable since TBTF institutions are by far more leveraged. But also for commercial banks with a very similar evolution in market leverage, the spread in interest expenses is substantial. The spread between the average cost of funds for smaller (Non-TBTF) banks and the costs of funds for institutions identified as TBTF averaged 0.4 percentage points for the whole period. In the period from the first quarter 2004 through the fourth quarter of 2007 the spread was 0.21%, then it increased to 0.79% at average for the last two years. This spread evolution is consistent with the results of Baker and McArthur (2009), where they use data of cost of funds from the FDIC and obtain average spreads of 0.29% (2000-2007) and 0.78% for 2008 4Q - 2009 2Q. They state that if this gap is attributable to the government guarantee[17], it implies a taxpayer subsidy for the TBTF banks. These banks are able to borrow at a much lower cost than other institutions who must borrow based on their own credit worthiness. For a better illustration I plot in Figure 1 the numbers for the commercial banks. In the left panel we

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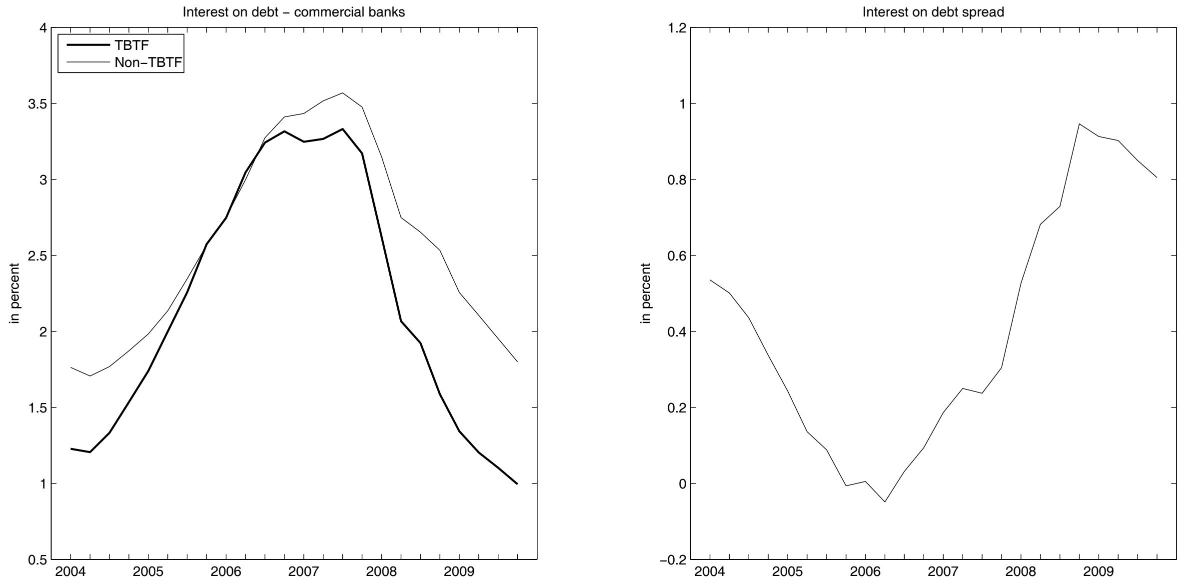
[15] One of the problems during the financial crisis was the short term financing of banks.

[16] In September 2008, Fannie Mae and Freddie Mac were placed into conservatorship by the United States Treasury Department (see Figure 4 or `http://www.treasury.gov/initiatives/financial-stability`). The role of GSEs and the evidence about their refinancing advantage are often discussed, for instance, Passmore (2005) or Lucas and McDonald (2006).

[17] With the Troubled Asset Relief Program and other rescue measures for distressed banks the U.S. government essentially introduced an official policy for TBTF banks. On the other hand, other explanations as a better diversification can induce a lower risk profile and therefore lower risk premiums. I examine this problem in the next section.

see the computed average interest rates on debt from Non-TBTF and TBTF commercial banks, $\bar{r}^d_{t,NTB}$ and $\bar{r}^d_{t,TB}$ for $t \in \{2004\ 1\text{Q}, \ldots, 2009\ 4\text{Q}\}$ respectively. In the right panel I calculate the difference $r^{d,\text{spread}}_t$ between the two curves.

Figure 1: Interest on debt evolution for commercial banks. Interest on debt refers to the ratio of annualized interest and related expenses to total liabilities at the end of each quarter. The left panel depicts the interest on debt development of both Non-TBTF and TBTF commercial banks, separately. In the right panel, the difference between the rates is plotted.



5 Empirical results

In this section I analyze the introduced objects which on the hand should reflect the TBTF or Non-TBTF status of a financial institution as refinancing advantage, differences in the asset volatility or the relative guarantee value spread. On the other hand I have a closer look on the absolute guarantee premiums for the identified TBTF institutions and the impact of stronger capital requirements.

5.1 Refinancing advantage

As already seen in the last paragraph of Subsection 4.2, the descriptive statistics of the interest expenses indicate that TBTF institutions are able to refinance under better (cheaper) conditions as the Non-TBTF competitors. Here, I investigate this relation more closely using annualized quarterly interest expenses on debt as dependent variable. My goal is to find evidence that TBTF banks actually have the possibility to refinance under cheaper conditions only because of the ‘too big to fail’ status they have.

Variables and predictions

I concentrate on commercial banks. Analog to Baker and McArthur (2009), I divide the time period into the quiet phase from 2004-2007 and the stress period 2008-2009. Latter period can be seen as the phase where the TBTF policy by the U.S. government became official (see before).

In a first step I regress interest expenses r_t^d on a dummy variable which equals one if the bank is TBTF and zero if not. The first regression equation is given by

$$r_t^d = \alpha + \beta_1 \text{ Dummy-TBTF}_t + \epsilon_t. \tag{11}$$

In the second step I additionally control for several variables which influence refinancing costs and investigate whether the dummy is still identified as significant. In the following, I present the control variables individually, describe the relation to the dependent variable r_t^d (refinancing costs) and report the used proxies and data source. Note, the goal is not to explain the level of refinancing costs by all these independent variables but to control for these and then to isolate the effect of the TBTF status of a bank.

1. *Firm Leverage lev_t:* In the structural framework higher leverage implies higher default risk, therefore creditors will ask for a higher risk premium. We use the market leverage ratio introduced in 4.2.
2. *Volatility σ_E:* A higher volatility increases the probability of default and therefore the risk premium and thus the refinancing costs in total. We use the historical (last 60 days) equity volatility, σ_E, since it is available for all institutions instead of the implied volatility.
3. *Tier-1-Ratio:* Another proxy for how well banks are capitalized and how risky operating assets are, is the Tier-1-Ratio (core capital to risk-weighted assets). Commercial banks are obliged to report it. High values indicate a sound capital buffer and/or low risk on the asset side. This variable should be negatively related with costs for refinancing.
4. *Spot rate r_t:* The effect of a higher spot rate is an increase in the refinancing costs. I calculate for each quarter the average yield of the last 60 daily (10-year) Treasury yield curve rates taken from Datastream.
5. *Slope:* Analog to Collin-Dufresne, Goldstein, and Martin (2001), I define the slope of the yield curve as the difference between Datastream's 10-year and 2-year Benchmark Treasury yield. A positive slope is an indication for higher *future* short rates, a growing economy and therefore higher refinancing costs. On the other hand a downward sloping yield curve (2004 - 2Q 2007) is an indicator for a recession, consequently lower interest rates and refinancing costs which can be observed around one year later on average. We expect a countercyclical behavior.
6. *Spread:* I employ the difference between the yields of the Thomson Reuters U.S. Corporate Benchmark BBB bond index and the 7-year Treasury as an control variable approximating the credit risk during this period. Refinancing costs should be an increasing function of the credit spread where we have to keep in mind that lower spreads occur rather in booming economic and

high interest times.
7. *Bond Index:* Additional to the spread, I use the average coupon of a Barclays investment grade bond index also taken from Datastream as a proxy for refinancing costs of risky firms.
8. *Business Climate:* Beside these variables, I incorporate the S&P 500 Return as a proxy for the business climate. Better business climate should be reflected in higher interest rates but lower risk premiums.

Moreover, I control for firm size (the logarithm of total assets) and include some (additional) lagged variables since the refinancing costs have accumulated during the last quarter and are in particular dependent on the firm characteristics at the beginning of the respective quarter. The second regression equation is given by:

$$\begin{aligned} r_t^d &= \alpha + \beta_1\, log(\text{Assets}_t) + \beta_2\, r_t + \beta_3\, (r_t)^2 + \beta_4\, \text{Bond Index}_t + \beta_5\, \text{S\&P 500 Return}_t \\ &+ \beta_6\, \text{S\&P 500 Return}_{t-1} + \beta_7\, \text{Spread}_t + \beta_8\, \text{Slope}_t + \beta_9\, \sigma_{Et} + \beta_{10}\, \sigma_{Et-1} \\ &+ \beta_{11}\, lev_{t-1} + \beta_{12}\, \text{Dummy-TBTF}_t + \beta_{13}\, \text{Tier-1-Ratio}_t + \epsilon_t. \end{aligned} \tag{12}$$

Results

I summarize some of the main findings. The regression results of equation (11) are presented in Table 2:
a. In both periods the dummy variable is significant and negative, where during the stress period even at a significance level of 1% instead of 5% in the quiet period.

Table 2: Determinants of the refinancing cost level during the quiet (2004-2007) and stress period (2008-2009). This table presents the estimation results for the regression specified in equation (11). Associated Newey-West standard errors with a lag of two appear in parentheses beneath. ***, ** and *, denote the statistical significance of the estimates at the 1%, 5% and 10% level, respectively.

	Quiet period 2004-2007	Stress period 2008-2009
Intercept	2.654***	2.416***
	(0.0174)	(0.0201)
Dummy-TBTF_t	-0.221**	-0.762***
	(0.0904)	(0.100)
Observations	9,705	4,367
R^2	0.001	0.018

Estimation results of equation (12) are reported in Table 3:
b. The contemporaneous spot rate, bond index, S&P Return, slope, equity volatility and leverage exhibit the predicted signs at a 1% significance level.
c. The Tier-1-Ratio is statistically significant in the stress period.
d. The results for the business climate proxied by quarterly S&P 500 Returns are positive and significant. However, the coefficient for the lagged variable is negative in the quiet period.
e. The variable of my main interest is the TBTF-Dummy. During the years 2004-2007 the

Table 3: Determinants of the refinancing cost level during the quiet (2004-2007) and stress period (2008-2009). This table presents the estimation results for the regression specified in equation (12). Associated Newey-West standard errors with a lag of two appear in parentheses beneath. ***, ** and *, denote the statistical significance of the estimates at the 1%, 5% and 10% level, respectively.

	Quiet period 2004-2007	Stress period 2008-2009
Intercept	-26.98***	-8.857***
	(1.250)	(1.027)
$\log(\text{Assets}_t)$	-0.0146	-0.112***
	(0.00927)	(0.0122)
r_t	1.956***	1.163***
	(0.480)	(0.425)
r_t^2	-0.175***	-0.251***
	(0.0501)	(0.0657)
Bond Index_t	4.085***	2.099***
	(0.150)	(0.123)
S&P 500 Return_t	0.0125***	0.00517***
	(0.00207)	(0.00133)
S&P 500 Return_{t-1}	-0.00592***	0.0211***
	(0.00172)	(0.00252)
Spread_t	0.153***	-0.0793**
	(0.0439)	(0.0324)
Slope_t	-0.720***	-0.564***
	(0.0138)	(0.0455)
σ_{Et}	0.171***	0.00134***
	(0.0424)	(0.000255)
σ_{Et-1}	0.00159***	0.000400
	(0.000396)	(0.000304)
lev_{t-1}	0.0354***	0.0196***
	(0.00285)	(0.00446)
Dummy-TBTF_t	-0.0548	-0.206**
	(0.0518)	(0.0854)
Tier-1-Ratio_t	-0.00376	-0.0283***
	(0.00412)	(0.00639)
Observations	7,606	3,947
R^2	0.656	0.451

coefficient is negative but not statistically. Entering the stress period the respective coefficient becomes significant and negative. This result supports the hypothesis that TBTF banks were able to refinance under better conditions than their competitors during the time the U.S. government implemented an official TBTF policy.

Robustness

All standard errors are estimated by using the modified Newey-West procedure for panel data accounting for the serial correlation of the residuals in the same cluster (see Petersen (2009)). Here, I report the results for the case where each cluster corresponds to a bank (fixed firm-effect). Alternatively, I account for the time-effect by setting the time variable as cluster and increase the lag to five (see Table 11). Moreover, I also conduct the benchmark regression with time dummies for addressing a potential additional time effect. All specifications do not change the direction of the initial result: the TBTF-Dummy is insignificant (or slightly significant in

Table 11) during the quiet period and then becomes statistically and economically significant. I modify our regression equation with respect to different variables. First, I replace the market by the accounting leverage ratio, the 10-year Treasury yield by the 1-year Treasury yield or Federal Fund Target rate, where I take out the variable Slope because of a very high correlation. Then I also include the S&P 500 Returns from the last year (lag 4). All these changes do not influence qualitatively the results when I control for the logarithm of assets. Additionally, I winsorize the interest expense data at the 2nd and 98th percentile, conduct the estimations and obtain similar results.

5.2 Asset volatility

As described above, initial market value of assets and asset volatility can be inferred by solving equations (8) and (9), where I choose the sum of initial market value of equity and book value of liabilities as a first guess for the market value of assets A_0. All starting values and solutions are scaled such that they are in the same range and therefore size independent. Later, I rescale the values and start the Monte Carlo simulation.[18] As noted, as benchmark I employ the historical equity volatility based on a rolling 60-day annualized standard deviation of equity price changes but later also report and discuss changes in the results for a 252-day historical equity volatility. All variables are winsorized at the 2nd and 98th percentile at each quarter across all banks (independent of TBTF or not).[19]

A detailed overview of the results for the asset volatility for all financial firms, the important subclass of commercial banks and a comparison of the average asset volatility between all three subclasses is given in the Tables 12, 13 and 14 in the Appendix, respectively. In Figure 2 I depict the asset volatility evolution across all subsets.

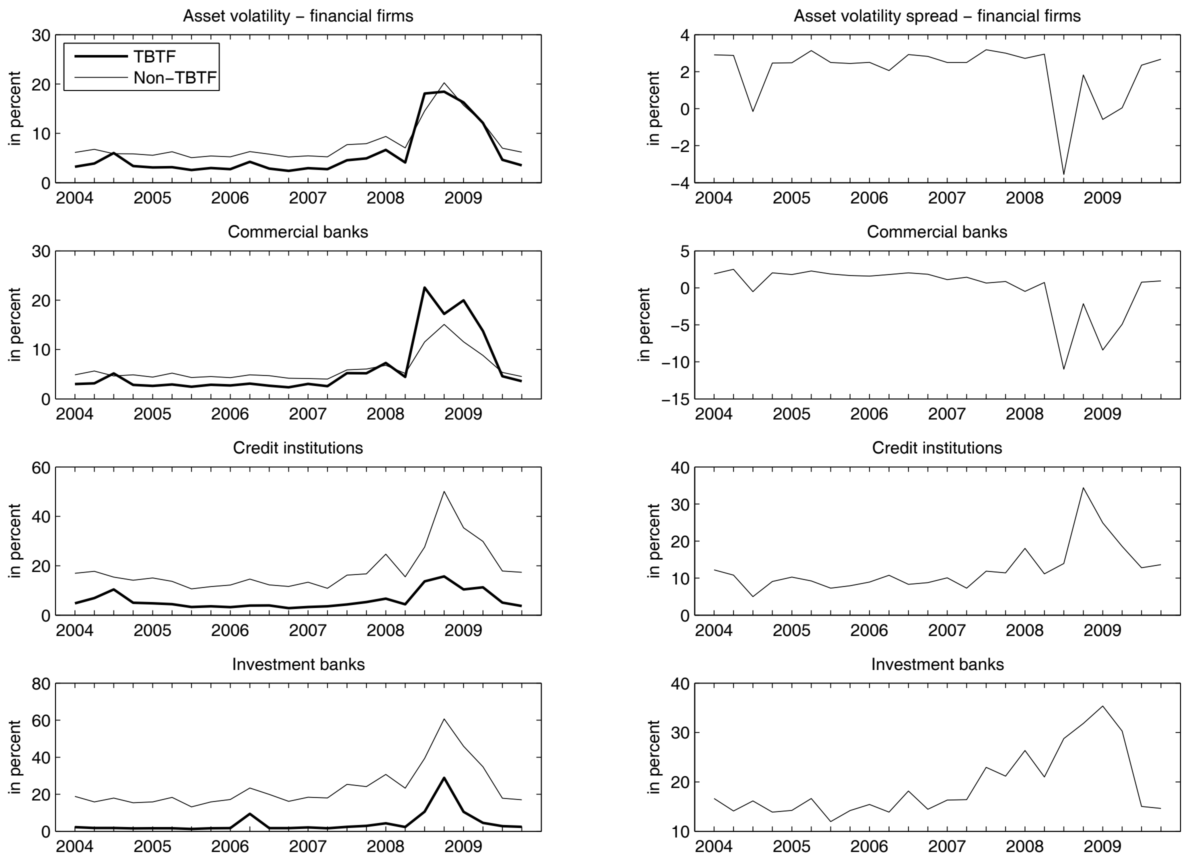
Some general comments: first, not astonishing we see a steep increase of the asset volatility of all financial firms during the years of the crisis (2008-2009) and a recurrence to levels as observed before the crisis at the last two quarters of 2009 (see Figure 2). Second, across the three subsets of Non-TBTF financials, asset volatility levels are almost always increasing from commercial banks over credit institutions to investment banks (see Table 14) which reflects the reverse relation of leverage ratios. Here, Non-TBTF commercial banks have the highest leverage ratios. This result is in line with Bohn and Crosbie (2003) who state that firms with more stable asset values can afford higher leverage levels than uncertain businesses or in other words leverage has an enlarging effect on asset volatility. Third, this mentioned relation can be partially observed for TBTF firms. TBTF investment banks are most highly leveraged and exhibit the lowest asset volatility (except 2006 2Q and 2008 4Q). Note, the sample sizes for each

[18]We exploit the MATLAB routine `lsqnonlin` and ensure that A_0 and σ_A are in the same range. I also checked the results when I rescale the values after the simulation. Guarantee values are slightly higher; I chose the more conservative approach.

[19]By winsorizing the estimation results for asset volatility we loose for instance the extreme high volatility value of Wachovia in the fourth quarter of 2008, where the bank was acquired by Wells Fargo.

category are very small and therefore the explanatory power is very limited. Fourth, if we compare asset volatility levels of Non-TBTF and TBTF firms of all financial firms but also within each subclass, we notice that with few exceptions the asset volatility of TBTF institutions is smaller than of Non-TBTF firms. This observation is also consistent with the findings of Bohn and Crosbie (2003) who document a negative correlation between firm size and asset volatility. TBTF banks are naturally the biggest institutions. Therefore, it is remarkable that this relation is reversed for commercial banks during the crisis: we observe a decreasing spread since 2007 and then high negative values for 2008 and the first two quarters of 2009. In Table 15 in the

Figure 2: First panel: Asset volatility of Non-TBTF and TBTF banks across financial firms and all subclasses. Second panel: difference in the respective asset volatility of Non-TBTF and TBTF banks. The values are obtained by solving equations (8) and (9) using a calculated rolling 60-day annualized standard deviation of equity price changes (historical equity volatility), time to maturity of one year and market capitalization, total liabilities and dividend yield reported at the end of each quarter. All variables are winsorized at the 2nd and 98th percentile at each quarter across all banks (independent of TBTF or not).



Appendix, I report the results for the asset volatility estimation based on a historical equity volatility of one year. Longer time horizons naturally smooth the volatility evolution: erratic changes become less important, but more persistent, with a longer time horizon. For instance, the peak in asset volatility of TBTF investment banks for the 60-day (252-day) specification is reached with 28.86% (14.34%) in 2008 4Q (2009 2Q). Therefore, the maximum value is strongly reduced and occurs two quarters later. The values around the peak reach in the one year case similar or slightly higher levels.

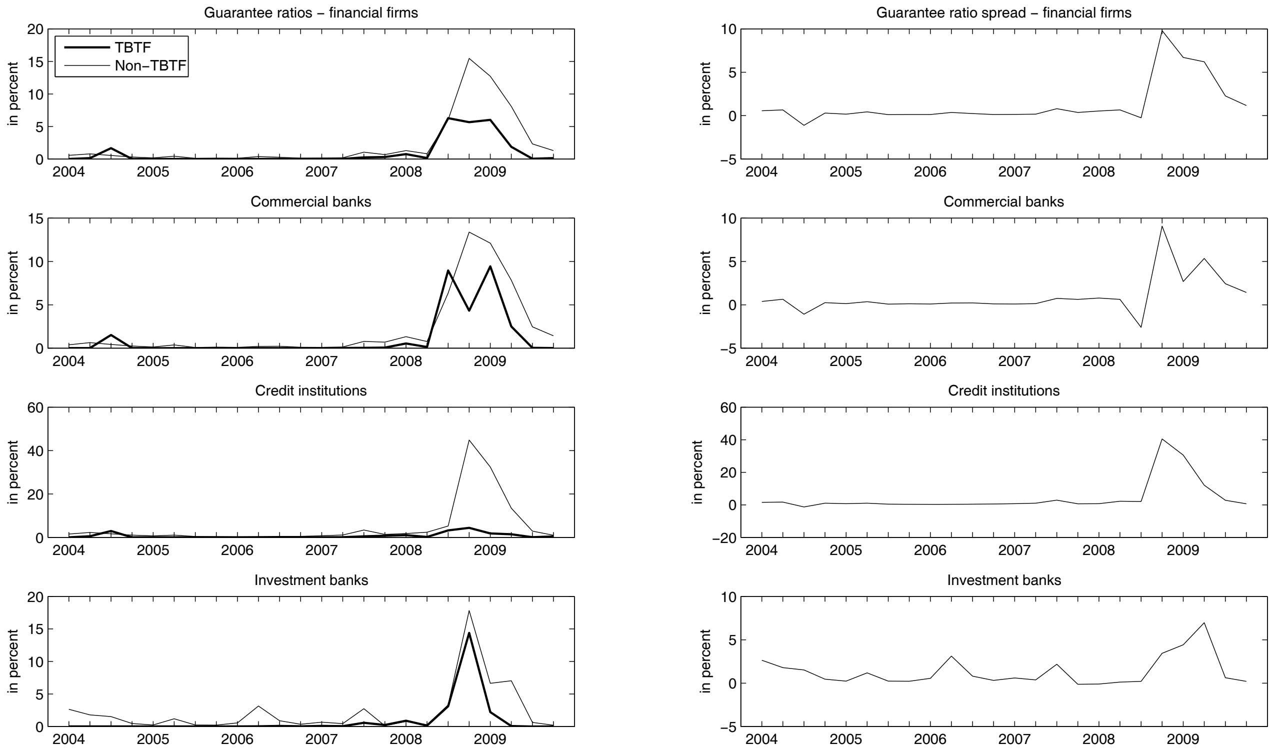
5.3 Guarantee values

In Subsections 3.1 and 3.4 I described the idea of calculating a liability insurance premium tailored for financial institutions. I present the results of this simulation study for the U.S. financial sector under consideration in the next paragraphs. To compare the different magnitudes across all banks, I express the simulated premiums as fractions of total assets in the first part. Then I study the absolute levels. Here, I concentrate on the identified TBTF institutions since their premiums are in particular relevant for the government or more general the tax payers. In the last part I quantify the impact of higher capital requirements on guarantee premiums. In general, I calculate premiums for a liability insurance with a contract period of one year, where I do this quarterly to illustrate premium dynamics by capturing changes in the underlying variables.

Guarantee value ratios

The relative guarantee value is set as ratio of simulated guarantee value to initial total assets. The average values for TBTF and Non-TBTF banks can be found in the Table 17 and in Figure 3. We see on the left side the average relative guarantee values of both sets of banks. In the right panel, the spread dynamic of the averaged estimated relative guarantee values from the first panel is plotted. Note, in contrast to all other objects I analyzed up to now, the guarantee values – and therefore also these relative expressions – are dependent on a multiplicity of influencing variables which makes it difficult to identify ultimately the relevant drivers of this evolution. We see that the volatility plays an important role but is not sufficient to explain all of the variation. First, we observe that for all subclasses and therefore also on the aggregate level the spread is mostly positive, i.e., Non-TBTF financial firms would have to pay on average more in relation to their total asset side than TBTF-banks for a guarantee. For financial firms (commercial banks), the average spread for the whole period is 1.28% (1.07%). In the period from the first quarter 2004 through the fourth quarter of 2007 the spread was 0.23% (0.26%) on average, then it increased to 3.39% (2.70%) for the last two years. For the time of the crisis the premiums for TBTF banks are strongly reduced. If the gap is attributable to the TBTF policy of the U.S. government, one can argue that the policy was successful in the sense that the implicit government guarantee was relatively lower than for the rest of the studied financial sector. In the years 2008 and 2009, the average amount of total assets of the TBTF financial firms (commercial banks) was around \$568 bn (\$548 bn), therefore the spread corresponds to an absolute value of about \$19.25 bn (\$14.8 bn) per year. Second, if we compare the numbers to the results of the asset volatility section (in particular Figure 2) we see on the one hand a very similar pattern of both evolutions. On the other hand, for the subset of commercial banks relative guarantee values of TBTF banks

Figure 3: First panel: development of relative guarantee values of financial firms and its composition across all subclasses. Second panel: difference in the respective relative guarantee levels of Non-TBTF and TBTF banks. Relative guarantee value refers to the ratio of guarantee value to initial total assets. The guarantee values for each bank are obtained by using the simulation approach described in Subsection 3.4 with an assumed debt maturity of one year and a 60-day historical equity volatility. All variables are winsorized at the 2nd and 98th percentile at each quarter across all banks (independent of TBTF or not).

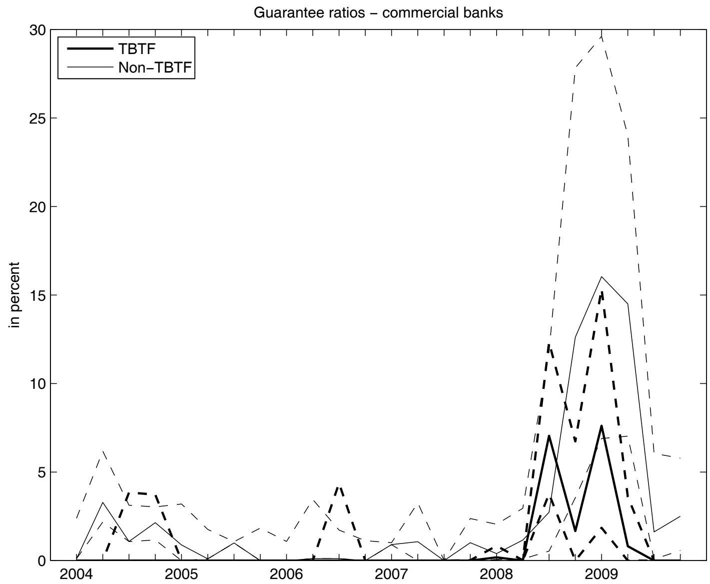


are lower than from Non-TBTF during the crisis, although the asset volatility is much higher. We have in mind that at the same time the interest on debt spread increases significantly (see Figure 1) which determines in our framework the future debt repayments, i.e., Non-TBTF banks have higher outstanding liabilities which possibly compensates the effect of a higher uncertainty expressed in the volatility. In Figure 4, median, 25%- and 75% quantiles of the simulated Monte Carlo distributions of commercial banks are plotted. During the quiet period, a clear separation of the two groups is not possible. In 2008-2009, the 75% quantiles of TBTF banks is permanently below the respective Non-TBTF values. In particular starting at 2008 4Q, the 75% quantile of TBTF banks is even below the Non-TBTF median of relative guarantee values.

Absolute guarantee values

Figure 5 and Table 16 present the evolution of absolute guarantee values of all TBTF financial firms and its composition across the different subclasses. The similarity to the left panel of Figure 2 is apparent and shows the strong impact of the asset volatility on the simulation results.

Figure 4: Development of relative guarantee values across TBTF and Non-TBTF commercial banks with 25%-, 50%- and 75%- confidence intervals. Relative guarantee value refers to the ratio of guarantee value to initial total assets. The guarantee values for each bank are obtained by using the simulation approach described in Subsection 3.4 with an assumed debt maturity of one year and a 60-day historical equity volatility. All variables are winsorized at the 2nd and 98th percentile at each quarter across all banks (independent of TBTF or not). The confidence intervals (dotted lines) are obtained from the quantiles of the simulated distribution.

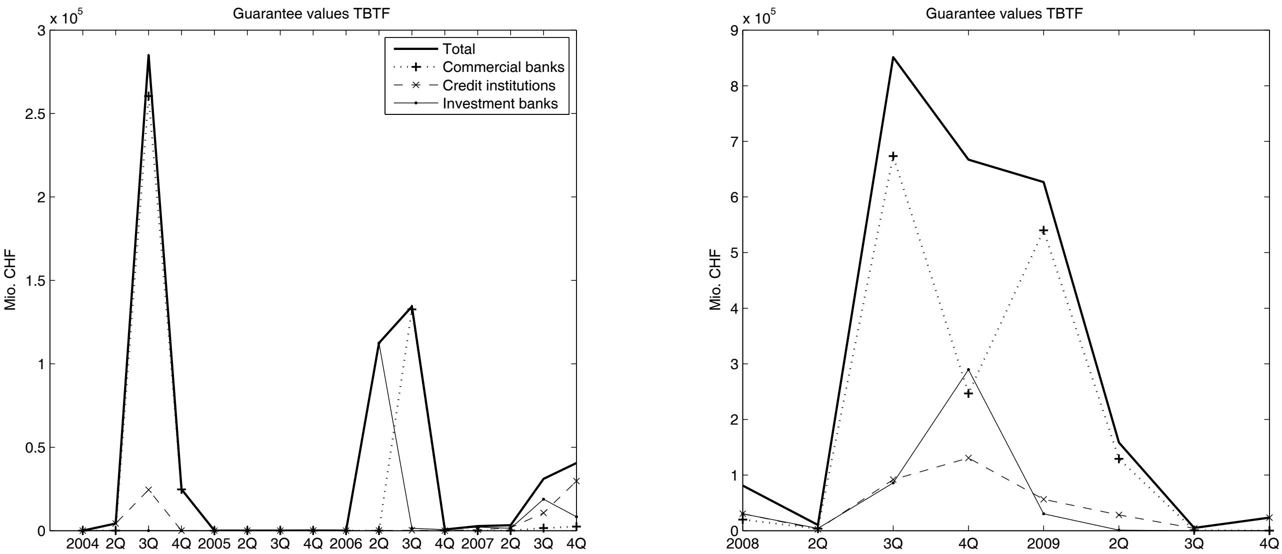


For instance, between the second quarter of 2008 and the first quarter of 2009 we observe a development in guarantee values which is exactly reflected in the asset volatility dynamic. In 2008 3Q, guarantee values of TBTF commercial banks capture about 80% of the total amount and the corresponding asset volatility is much higher than for TBTF credit institutions or investment banks. For commercial banks, a drop in guarantee value coverage (down to 37%) and asset volatility follows the next quarter. In contrast, due to the turmoil during this quarter (failure of Lehman Brothers and acquisition of Merrill Lynch, see Table 4) TBTF investment banks end with a tripled asset volatility and a resulting 44% fraction of the total guarantee value. This is even more remarkable since during this time they only represented almost 17% of total assets from TBTF financial firms.[20] In the third quarter 2008 the total premium amount reaches a maximum of $850 bn. For the considered time period the average liability insurance premium for all TBTF financial firms equals approx. $128 bn per year. This number relates to an average amount of $12.4 trillion of aggregated total assets of all TBTF financial firms during 2004-2009.

In the panel at the bottom of Table 16, I also report guarantee value levels using a 252-day historical equity volatility for approximating the asset volatility. In Subsection 5.2 I already

[20]In the Appendix, Table 8, I calculate the total asset distribution with respect to total assets of all financial firms (Non-TBTF and TBTF). Here, I adjust the fraction for TBTF total assets.

Figure 5: Development of absolute guarantee values of TBTF financial firms (total) and its composition across all subclasses.



pointed out the smoothening effect of a longer time horizon for calculating the equity volatility and then estimating the asset volatility, which has a strong impact on guarantee value levels. Comparing both volatility specifications: the peak of the premium evolution of all TBTF financial firms moves from the third quarter of 2008 to the third quarter 2009, where the maximum is now at around \$400 bn. I obtain now \$69 bn for the average premium compared to \$128 billion before.

Increased equity capital requirements

In the aftermath of the crisis a lot of regulatory measures are discussed and some were already implemented. In Basel, supervisory authorities discuss and decide about a third regulatory standard for financial institutions around the globe (Basel Committee on Banking Supervision (2011)). In particular, higher and anticyclical capital requirements, a supplementary leverage ratio (not based on risk-weighted assets) or extended liquidity standards are on the agenda.[21] In Switzerland the authorities already decided about the implementation of some specific measures, among others contingent capital – debt which converts to equity (bail-in) in certain predefined

[21] A compilation of documents related to the regulatory process can be found under `http://www.bis.org/list/basel3/page_1.htm`.

events – to strengthen the capital basis in situations where banks are under pressure.[22] With the proposed methodology in this paper it is neither possible to test liquidity measures (because it is a solvency framework) nor complex liability structures as they appear for convertible bonds. However, an often requested very simple regulatory measure is the increase of an unweighted equity ratio, i.e., equity relative to total assets (not risk weighted). Admati, DeMarzo, Hellwig, and Pfleiderer (2011) state that 'equity capital ratios as high as 20% or 30% on an unweighted basis should not be unthinkable'. Therefore, I study the consequences of this proposal on the liability insurance premiums for the TBTF financial firms on the sample. Note: first, the sample of TBTF institutions can possibly change through time and I identified these financial institutions ex-post. Second, it is not clear at all that only very big institutions are TBTF. It is imaginable that a number of smaller institutions default at the same time which also makes governmental interventions necessary. Moreover, I think that it is not possible for the government to commit to never bail out a bank. The goal is to approximate the guarantee evolution through time and to determine the reduced magnitudes by implementing higher capital requirements. I operationalize the assumption of increased capital requirements in the simulation by decreasing the target liability to asset ratio to 70%. Since another regulatory regime – namely Basel II – is in place, a lot of institutions have initial equity to asset ratios much lower than proposed by latter authors. Therefore, especially the highly leveraged institutions will have to deleverage massively during the simulation.

Table 18 provides the respective results for the guarantee values relative to initial total assets across all subclasses of financial institutions and Table 19 presents the absolute values of all TBTF financial firms. As expected, all values are reduced. Defaults will occur less often and in that case the costs for the guarantor are lower because of higher liable equity. In both tables the reduction is more pronounced for lower values. For instance, the relative (absolute) guarantee value of all TBTF financial firms at its peak in 2008 3Q is reduced by 30%, whereas in 2004 2Q the initial much lower values decrease by around 60%.

Accumulating the reductions of relative premiums and comparing these between Non-TBTF and TBTF (in parentheses) financial firms, we observe an average decline of 0.31% (0.06%) in the years 2004-2007 and of 3.23% (0.94%) for 2008-2009, respectively. In other words, Non-TBTF financial firms following a target liability to asset ratio of 70% should have paid a lower (compared to the Basel II benchmark) insurance premium during the crisis of 3.23% in terms of total assets. Of course the premium levels of both groups are very different as seen above (Figure

[22]Currently, the legislative authorities have to put the proposals from an expert commission into law, but it is intended that a conversion takes place in the event that equity is lower than 5% of the risk weighted assets. Details about this process can be found on the page of the financial treasury `http://www.efd.admin.ch/themen/00796/02235/index.html?lang=de`. Some critical remarks regarding this way of strengthening the capital basis can be found in Admati, DeMarzo, Hellwig, and Pfleiderer (2011), pp. 53, or Bürgi ('Knifflige Preisfindung für CoCos', Neue Zürcher Zeitung, March 29, 2011).
Haefeli and Jüttner (2010) examine also other discussed regulatory measures as more audits. Moreover, we give more details about the robustness of this simulation approach to other parameter specifications. Due to the length of this elaboration we have to refer the interested reader to our former work.

3). Therefore, it makes sense to compare these absolute changes in the ratios in relative terms to the benchmark ratio. During the first period (2004-2007) Non-TBTF and TBTF financial firms reached in the benchmark case (Table 17) average premium levels of 0.38% (0.15%) and during the crisis (2008-2009) around 6% (2.62%), respectively. Therefore, the change in the liability to asset ratio induces an average percental reduction during 2004-2007 of 83% (42%) and for 2008-2009 of 54% (36%) for Non-TBTF and TBTF (in parentheses) financial firms.

Analog to the discussion above regarding the absolute guarantee values of TBTF institutions, I consider also in this modified case the effects on the aggregated premium amount of the TBTF sector. Naturally, we observe a reduction in all values where the composition across the different subclasses is quite similar. For the whole time period the average premium is now $76 billion (compared to the $128 bn before). For 2004-2007 an average of $29 bn and for the crisis $170 bn are obtained.

We see that within this model framework the simple measure of increasing the equity to asset ratio has a strong impact on insurance premiums across the financial sector. For Non-TBTF banks this effect is even stronger, but also for TBTF institutions the average amount can be reduced by around 40%, i.e., potential bailouts should be much cheaper for tax payers. However, introducing an unweighted leverage to asset ratio of 30% is a critical and difficult requirement. Regulators have to decide about timing and implementation design. Admati, DeMarzo, Hellwig, and Pfleiderer (2011) discuss this issue and provide possible solutions.

6 Conclusion

In this paper I revisit on the one hand some of the theoretical implications of the existence of systemic relevant banks on the market mechanism or market based variables as asset volatility. On the other hand, I compare and study two established ways for estimating the value of the induced implicit guarantee of 'too big to fail' banks in the United States from 2004-2009. First, by conducting a regression analysis, I find evidence that TBTF banks were able to refinance under cheaper conditions during the stress period 2008-2009. In the quiet period from 2004-2007 no statistically significant effect could be observed. The second part of the work deals with the contingent-claim approach which determines the fair risk premium for insuring the liability side of a financial institution. This approach uses market-based input parameters and therefore reflects the market perception about risk and future returns. As expected, also during the years 2008 and 2009, the premiums relative to total assets of the banks differ between Non-TBTF and TBTF banks. For all financial firms, the average difference in the relative guarantee levels of Non-TBTF and TBTF banks is 1.28% for the whole period. In the period from the first quarter 2004 through the fourth quarter of 2007 this spread was 0.23% on average, then it increased to 3.39% for the last two years. In other words, for the time of the crisis the premiums for TBTF banks are strongly reduced. This reduction corresponds to an absolute value of about $19.25 bn per year if I take into account the amount of total assets of TBTF institutions. A decrease in the liability to asset ratio to 70% induces an average percental reduction of liability insurance premiums for TBTF financial firms of around 40%.

The result about the endogeneity effect of the implicit guarantee on the estimation approach is essential for interpreting and comparing both approaches. From the regulatory point of view, it is in particular interesting to study the impact of higher capital requirements. The contingent-claim approach allows in contrast to the cash-flow approach the quantification of a regulatory change and shows the economic importance.

Appendix A Merton framework

The estimation of the asset volatility and the analysis of the liability insurance premiums across U.S. banks is based on Black and Scholes (1973) and Merton (1974), though the actual asset and liability paths for estimating the liability insurance premiums are simulated using the presented framework from Lucas and McDonald (2006). In contrast to latter authors where the default of a company possibly occurs during the debt maturity when the firm value falls below some default threshold, Merton (1974) assumes that the company defaults at time T when the company is not able to pay the contractual obligations. Furthermore, the Modigliani-Miller theorem holds, the value of the firm is independent of the capital structure where the assets are financed by a homogenous class of debt and equity.

I repeat some details of the framework and derive the used relationship between equity and asset volatility. First, the risk-neutral asset evolution is assumed to follow a geometric Brownian motion

$$dA_t = (r_f - q)A_t dt + \sigma_A A_t dZ_t, \tag{13}$$

where r_f is the risk-free rate, $q = \frac{\delta E}{A}$ the dividend yield on assets (δ the dividend yield on equity), σ_A denotes the asset volatility and $(Z_t)_t$ is a standard Brownian motion. Then it is supposed that another security can be expressed by a function of the value of the firm A and time, i.e., $E = F(A, t)$. Merton derives a PDE which has to be satisfied by any security dependent on A and t. The boundary conditions distinguish then different securities as equity or debt. The security can be evaluated with contingent-claim analysis; equity as a European call option on the underlying assets A and future book value of debt as the strike price L. The dynamics of E are given by a similar stochastic differential equation

$$dE_t = (r_f - \delta)E_t dt + \sigma_E E_t dW_t. \tag{14}$$

With Itô's Lemma we can write

$$\begin{aligned} dE_t &= F_A dA_t + \frac{1}{2}F_{AA}(dA_t)^2 + F_t dt \\ &= F_A((r_f - q)A_t dt + \sigma_A A_t dZ_t) + \frac{1}{2}F_{AA}\sigma_A^2 A_t^2 dt + F_t dt \\ &= \big[\frac{1}{2}F_{AA}\sigma_A^2 A_t^2 + (r_f - q)A_t F_A + F_t\big]dt + \sigma_A A_t F_A dZ_t, \end{aligned} \tag{15}$$

where F_A (F_{AA}) denotes the first (second) derivative of F with respect to A. Comparing equations (14) and (15) we have

$$r_f E_t = r_f F_t = \frac{1}{2}F_{AA}\sigma_A^2 A_t^2 + (r_f - q)A_t F_A + F_t + qA_t \tag{16}$$

$$\sigma_E E_t = \sigma_E F_t = \sigma_A A_t F_A \tag{17}$$

$$dW_t = dZ_t. \tag{18}$$

With equation (17) we obtain

$$\sigma_A = \sigma_E \frac{E_t}{A_t}(F_A)^{-1}, \tag{19}$$

therefore left to determine F which is in this context the value of an European call option C which is given by

$$C(A_0, 0) = \mathbf{E}_{\mathbb{Q}}[e^{-r_f T}(A_T - D_T)^+],$$

where $\mathbb{Q}$ is the risk neutral measure, A_T the firm value at the debt maturity date T and D_T the promised payment to debtholders. The result of this equation for stocks with dividends is well known (see e.g. Shreve (2005)) and given by

$$\begin{aligned} E_0 &= A_0 e^{-qT} N(d_1) - D_T e^{-r_f T} N(d_2) \qquad (20)\\ d_1 &= (\log(A_0/D_T) + (r_f - q + \frac{\sigma_A^2}{2})T)/(\sigma_A \sqrt{T}),\\ d_2 &= d_1 - \sigma_A \sqrt{T}, \end{aligned}$$

where the dividends shareholders receive up to time T with rate $dA_t = qA_t dt$ have to be incorporated, i.e., accumulated over $[0, T]$:

$$\int_0^T A_0 q e^{-qt} dt = A_0(1 - e^{-qT}). \tag{21}$$

In each time step dividends q are paid out to shareholders and therefore the asset value decreases accordingly. After adding (21) to equation (20), the first derivative with respect to A in equation (19) can be calculated to establish the relationship between σ_A and σ_E.

Appendix B Repeated debt guarantee - Lucas and McDonald (2009)

For convenience I present the elaboration of Lucas and McDonald (2009). They use the following notation: $X_m(t)$ is the value of X at time $mT + t$, where $m \in \mathbb{N}_0$. Each period has length T. To describe the framework with compact and interpretable expressions Lucas and McDonald (2009) use a stationary framework where they have to impose some very strong assumptions. First, it is assumed that the target leverage ratio is fixed, therefore the decision about the issuing debt amount is exogenous. At the beginning of each period mT the bank issues debt such that

$$D_m(T) = \gamma e^{r_f T} A_m(0), \tag{22}$$

where $D_m(T)$ is the debt value at $mT + T$ (at the end of the respective period), $A_m(0)$ the asset value at time mT and $\gamma e^{r_f T}$ represents the constant leverage ratio. Then it is possible with equations (3) and (22) to express the guarantee value for an insured institution for one period at each reset date mT proportional to the asset value:

$$\begin{aligned} g_m = \frac{G_m(0)}{A_m(0)} &= \frac{D^I_m(0) - D^U_m(0)}{A_m(0)} \\ &= \frac{e^{-r_f T}\mathbf{E}_m[\max\{D_m(T) - A_m(T), 0\}]}{A_m(0)} \\ &= \frac{\mathbf{E}_m[\max\{\gamma A_m(0) - e^{-r_f T} A_m(T), 0\}]}{A_m(0)} \\ &= \mathbf{E}_m[\max\{\gamma - \frac{e^{-r_f T} A_m(T)}{A_m(0)}, 0\}]. \end{aligned}$$

Note, the guarantee value in each period is just dependent on the expectation regarding the evolution of operating assets, because also in cases where operating assets are not sufficient and shareholders do not decide to default, debtholders receive the outstanding liabilities (the difference between debt and operating assets) but then not paid from the guarantor but from existing shareholders. In each case debtholders are insured and therefore do not require the associated risk premium. This results on the one hand in a dividend stream for shareholders, because each period they do not default they are able to issue again secured debt, on the other hand in a cost stream, because there are states where they pay the outstanding amount to be able to realize expected future rewards from the guarantee.

Let p^j_m, $j \in \{I, U\}$ denote the risk-neutral probability, conditional on the information set at time mT, that bank j does not declare bankruptcy at the end of this period $(m+1)T$. As already noted: for the uninsured institution U this is $\mathbf{P}_m[A_{m+1}(0) > D_m(T)]$, for the insured bank I the continuity condition is more intricated and will be explained later. Since the guarantee value is expressed as a ratio of total assets and total assets increase through time, the value has to be scaled by the expected asset growth rate of the period under consideration. The term λ_m denotes the expectation of the asset growth rate for the period $[(m+1)T, (m+2)T]$ conditional on 'no bankruptcy' at time $(m+1)T$.[23]
Lucas and McDonald (2009) assume a stationary environment, i.e., they can omit the time indices. Each period has the same distributional properties where up to now any stochastic dynamics were not specified. The value of the *dividend stream* starting with current asset value A, is then:

$$\Gamma A = gA \sum_{i=0}^{\infty} e^{-r_f\, iT} (\lambda^I\, p^I)^i. \tag{23}$$

The counterpart of the dividend stream is the cost component which arises in states of the world where uninsured firms would declare bankruptcy, but shareholders of insured institutions

[23]Here I want to be clear about the time structure of the different introduced elements, whereas in the stationary framework the differences do not matter. For instance, to be able to issue secured debt at time $2T$, the bank has to stay in business at $2T$, the associated probability is p_1 (so the position is time T). The discounted expected guarantee ratio at time $2T$ is denoted by g_2 where the guarantee refers to period $[2T, 2T+T]$. Therefore, the relevant survival probability is $p_1(0)$. For this guarantee value the asset growth rate is essential and is denoted by λ_1, that is the expected asset growth rate for period $[2T, 3T]$ under the condition that the institution is not defaulted at time $2T$. This notation is drawn from Lucas and McDonald (2009).

repay the debt amount to stay in business. Again only one period is considered and then the stationarity condition is used for more periods. At time mT the expected cost component expressed as a ratio of total assets $\eta A_m(0)$ is given by

$$\eta A_m(0) = \int_{A_m(0)(\gamma e^{r_f T} - \Gamma + H)}^{D_m(T)} \left(\gamma e^{r_f T} A_m(0) - \alpha f(\alpha | A_m(0))\right) d\alpha, \tag{24}$$

where $f(\alpha|A_m(0))$ is the density function of asset value $A_m(T)$, at time $(m+1)T$, conditional on the asset value at time mT, H is the cost component describing the expected repaying of shareholders to debtholders in the subsequent periods. Therefore, at the beginning of each period shareholders are expected to pay outstanding liabilities at the end of the specific period if they not exceed the potential expected benefits of repeated debt guarantees in the future ΓA less the incidental expected costs HA. This is expressed in the integral boundaries: only total asset levels between $A_m(0)(\gamma e^{r_f T} - \Gamma + H)$ and $D_m(T)$ are included in the calculation. If the dividend stream associated with secured debt ΓA is higher, shareholders are willing to pay more in order to realize these future rents. As before, also the *cost component* is dependent on the survival probability and has to be scaled by the asset growth rate:

$$HA = \eta A \sum_{i=0}^{\infty} e^{-r_f T} (\lambda^I p^I)^i. \tag{25}$$

All in all, Lucas and McDonald (2009) have introduced two objects which are fundamental to understand the difference between insured and uninsured institutions: dividend and cost stream. Now they are able to specify the continuity condition for an insured institution: at each debt reset date mT the survival probability of an insured firm is given by $\mathbf{P}_m[A_{m+1}(0)(1+\Gamma-H) > D_m(T)]$. With this insight market assets on a debt reset date are defined as $A_m^*(0) = A_m(0)(1+\Gamma-H)$. The market asset volatility is then proportional to the asset volatility of operating assets, i.e., $\sigma_{A^*} = \sigma_A(1+\Gamma-H)$.

Appendix C Tables and figures

Table 4: Time line with events during the considered period 2004-2009.

Date	**Event**	**Description**
May 2006	Acquisition of Golden West by Wachovia	On May 7 the acquisition is announced. The financial statements end at the second quarter of 2006. Golden West Financial reports total assets of about $129 billion at this time.
January-July 2008	Acquisition of Countrywide by Bank of America	On January 11 announcement to purchase Countrywide Financial. After the approval of the Fed and shareholders the acquisition is completed in July. End of March total assets amount for $199 billion.
March 2008	Term Auction Facility (TAF) & Fed facilitates Financing	The Federal Reserve Board announces $50 billion Term Auction Facility (TAF) auctions and extends the TAF for at least 6 months. The Federal Reserve Bank of New York announces that it will provide term financing to facilitate JPMorgan Chase & Co.'s acquisition of The Bear Stearns Companies Inc.
September 2008	Conservatorship for Fannie Mae and Freddie Mac	On September 7 announcement of James B. Lockhart from the Federal Housing Finance Agency (FHFA) that the U.S. Treasury (through the FHFA) will act as the conservator to operate the enterprises until they are stabilized.
September 2008	Failure of Lehman Brothers	On September 15 Lehman Brothers files for Chapter 11 bankruptcy protection.
September 2008	Failure of Washington Mutual	On September 25 the banking operations of Washington Mutual Inc. are sold in a transaction facilitated by the Office of Thrift Supervision and the Federal Deposit Insurance Corporation to JPMorgan Chase for $1.9 billion. Claims by equity, subordinated and senior debt holders are not acquired. End of June Washington mutual reports total assets of $310 billion.
September 2008 - January 2009	Acquisition of Merrill Lynch by Bank of America	On September 14 Merrill agreed to a purchase by the Bank of America. In January it ceased to exist as a separate entity. End of 2008 total assets added up to $668 billion.
October 2008	Acquisition of Wachovia by Wells Fargo	On October 3 they agree to merge in an all-stock transaction. At the end of the third quarter Wachovia reports total assets of $764 billion, which is at this time the seventh largest amount across U.S. banks.
October 2008	Acquisition of National City by PNC	On October 24 PNC announces that it has finalized a purchase agreement for National City. The total assets of National City add up to $144 billion at 3Q 2008.
February-May 2009	Stress Capital Assistance Program	Stress test for the largest domestic bank holding companies using a common set of scenarios and conceptual framework. On May 7 the results reveal an aggregate gap of $75 billion. Banks which deem inadequately capitalized are automatically qualified for funds of the Capital Assistance Plan.

Table 5: Industry classification and number of banks in each category. A (*) indicates an industry in which financial institutions report a Tier-1 ratio.

Financial Institutions	2-digit SIC	SIC Code	Financial Service Industry	Number
Depository Institutions	60	6020	Commercial Banks*	527
		6035	Federal Savings Institutions*	169
		6036	Savings Institutions, Not Federally Chartered*	68
		6099	Functions Related to Depository Banking	15
Nondepository Credit Institutions	61	6111	Federal Credit Agencies	6
		6141	Personal Credit Institutions	18
		6153	Short-Term Business Credit Institutions	5
		6159	Miscellaneous Business Credit Institutions	14
		6162	Mortgage Bankers and Loan Correspondents	12
		6172	Finance Lessors	3
		6199	Finance Services	2
Investment Banks	62	6200	Security and Commodity Brokers, Dealers, Exchanges, and Services, et al.	12
		6211	Security Brokers, Dealers and Flotation Companies	39
		6282	Investment Advice	26
			Total	916

Table 6: TBTF banks and SIC classification.

Financial Institutions	SIC Code	Name
Depository Institutions		
Commercial Banks	6020	Bank of America Corp
		Bank of New York Mellon Corp
		BB&T Corp
		JP Morgan Chase
		Fifth Third Bancorp
		Keycorp
		National City Corp
		PNC Financial Services Group
		Regions Financial Corp
		State Street Corp
		Sunstrust Banks Inc
		US Bancorp
		Wachovia
		Wells Fargo & Co
Federal Savings Institutions	6035	Washington Mutual Inc
		Golden West Financial Corp
Nondepository Credit Institutions		
Federal Credit Agencies	6111	Centerline Holding Co
		Federal National Mortgage Association (Fannie Mae)
		Federal Agricultural Mortgage Corporation (Fama Mac)
		Federal Home Loan Mortgage Corporation (Freddie Mac)
		SLM Corporation (Sallie Mae)
		The Student Loan Corporation
Personal Credit Institutions	6141	Capital One Financial Corp
Mortgage Bankers and Loan Correspondents	6162	Countrywide Financial Corp
Finance Services	6199	American Express Co
		Citigroup Inc
Investment Banks		
Security Brokers and Dealers	6211	Goldman Sachs Group
		Lehman Brothers Holdings Inc
		Merrill Lynch & Co Inc
		Morgan Stanley

Table 7: Summary statistics of total assets, leverage ratio, equity volatility, Tier-1-Ratio and interest expenses. All measures refer to quarterly observations from 2004-2009 across all banks. N denotes the number of observations. Lev. Ratio (market leverage ratio) refers to the quotient of total liabilities and the sum of market value of equity and total liabilities. σ_E denotes equity volatility and is determined by calculating the rolling 60-day annualized standard deviation of equity price changes (historical equity volatility). Commercial banks have to report the Tier-1-Ratio which is defined as the ratio of core capital and risk weighted assets. Interest expenses are interest and related expenses in percentages of the reported total liabilities at the end of each quarter quadrupled to obtain annualized expressions. The term 'q' denotes the quantile, i.e., 10q refers to the 10th quantile in the empirical distribution of the particular variable.

	Total assets (in mio. USD)	**Lev. Ratio** in %	$\sigma_\mathbf{E}$ in %	**Tier-1-Ratio** in %	**Interest expenses** in %
Commercial banks					
Mean	13556.57	85.68	44.58	11.35	2.57
Median	1093.89	86.57	30.41	10.79	2.52
Std. Dev.	101665.5	9.37	39.89	3.42	1.00
10q	317.91	77.95	16.26	7.92	1.42
90q	10644.88	94.84	93.10	15.42	3.75
N	14072	14072	14072	11685	14072
Credit institutions					
Mean	76486.95	68.03	62.74	.	4.68
Median	1591.54	77.26	43.45	.	4.28
Std. Dev.	298575.3	27.51	58.47	.	4.51
10q	151.72	22.48	20.17	.	1.24
90q	97765.59	96.51	132.43	.	7.30
N	1026	1026	1026	0	1026
Investment banks					
Mean	63380.82	49.19	56.86	.	2.57
Median	1775.05	45.94	42.36	.	1.92
Std. Dev.	207564.2	30.85	44.36	.	4.48
10q	58.89	10.09	21.02	.	0.19
90q	53196.95	92.90	109.10	.	4.73
N	1165	1165	1165	0	1165
Total					
Mean	21095.88	81.96	46.61	11.35	2.70
Median	1126.529	86.07	31.87	10.79	2.55
Std. Dev.	134227.2	17.11	41.96	3.42	1.96
10q	299.564	69.39	16.66	7.92	1.31
90q	13821.7	94.79	96.79	15.42	3.98
N	16263	16263	16263	11685	16263

Table 8: Total asset distribution across commercial banks, credit institutions and investment banks. This table presents the average total asset amount of Non-TBTF and TBTF banks in each considered subset (commercial banks, depository institutions and investment banks) as a fraction of total assets of all financial firms in the sample in each quarter for the whole period. *N* denotes the number of observations.

	2004 1Q	2Q	3Q	4Q	2005 1Q	2Q	3Q	4Q	2006 1Q	2Q	3Q	4Q
Non-TBTF												
Commercial banks												
Total assets in %	22.75	19.12	18.45	18.44	18.24	17.40	18.22	16.23	16.92	16.88	16.94	14.74
N	586	586	586	592	595	604	605	602	601	600	598	593
Credit institutions												
Total assets in %	1.70	1.46	1.46	1.50	1.59	1.60	1.74	1.63	1.67	1.62	1.69	1.59
N	35	37	36	37	38	39	39	35	34	34	32	33
Investment banks												
Total assets in %	1.85	1.56	1.46	1.44	1.42	1.32	1.48	2.14	2.36	2.31	2.45	2.36
N	34	35	35	34	36	37	38	39	38	40	40	43
Financial firms												
Total assets in %	26.30	22.14	21.36	21.38	21.24	20.32	21.43	20.00	20.95	20.80	21.07	18.69
N	655	658	657	663	669	680	682	676	673	674	670	669
TBTF												
Commercial banks												
Total assets in %	46.54	40.56	42.47	42.15	42.42	39.44	42.22	39.07	41.46	41.16	40.04	37.73
N	16	16	16	16	16	16	16	16	16	16	15	15
Credit institutions												
Total assets in %	3.26	16.58	15.92	15.89	15.52	21.01	15.18	20.59	15.33	15.20	16.04	21.55
N	6	7	7	7	7	8	7	8	7	7	7	8
Investment banks												
Total assets in %	23.91	20.73	20.25	20.58	20.81	19.23	21.17	20.35	22.27	22.84	22.85	22.03
N	4	4	4	4	4	4	4	4	4	4	4	4
Financial firms												
Total assets in %	73.70	77.86	78.64	78.62	78.76	79.68	78.57	80.00	79.05	79.20	78.93	81.31
N	26	27	27	27	27	28	27	28	27	27	26	27

	2007 1Q	2Q	3Q	Q4	2008 1Q	2Q	3Q	4Q	2009 1Q	2Q	3Q	4Q
Non-TBTF												
Commercial banks												
Total assets in %	14.07	12.44	12.07	12.01	11.80	12.36	12.62	13.05	12.95	12.68	13.99	12.59
N	584	583	577	563	561	556	551	532	530	521	511	501
Credit institutions												
Total assets in %	1.60	1.51	1.44	1.34	1.34	1.11	1.12	1.15	1.12	1.08	1.16	0.53
N	34	36	37	36	35	35	36	33	33	33	32	29
Investment banks												
Total assets in %	2.42	2.43	2.68	3.01	2.78	2.86	3.01	3.03	3.11	3.47	4.08	4.64
N	47	45	50	52	53	54	53	53	57	56	56	55
Financial firms												
Total assets in %	18.10	16.39	16.19	16.36	15.92	16.33	16.75	17.24	17.19	17.23	19.22	17.76
N	665	664	664	651	649	645	640	618	620	610	599	585
TBTF												
Commercial banks												
Total assets in %	36.89	34.95	35.20	36.73	36.64	38.20	41.77	43.16	46.24	45.98	50.92	45.68
N	15	15	15	15	15	15	14	12	12	12	12	12
Credit institutions												
Total assets in %	21.69	26.13	25.88	24.99	24.88	24.52	24.47	25.94	26.70	26.72	23.55	26.14
N	8	9	9	9	10	9	9	8	8	8	7	8
Investment banks												
Total assets in %	23.32	22.53	22.73	21.92	22.56	20.96	17.01	13.67	9.87	10.07	6.31	10.41
N	4	4	4	4	4	4	3	3	2	2	1	2
Financial firms												
Total assets in %	81.90	83.61	83.81	83.64	84.08	83.67	83.25	82.76	82.81	82.77	80.78	82.24
N	27	28	28	28	29	28	26	23	22	22	20	22

Table 9: Market capitalization distribution across commercial banks, credit institutions and investment banks. This table presents the average market capitalization (market cap) of Non-TBTF and TBTF banks in each considered subset (commercial banks, depository institutions and investment banks) as a fraction of market capitalization of all financial firms in the sample at the end of each quarter for the whole time period. Market cap is the product of outstanding common shares and closing price at the end of the quarter. N denotes the number of observations.

	2004 1Q	2Q	3Q	4Q	2005 1Q	2Q	3Q	4Q	2006 1Q	2Q	3Q	4Q
Non-TBTF												
Commercial banks												
Market cap in %	28.20	23.78	23.43	23.61	23.26	23.26	23.69	20.49	20.78	20.58	20.68	19.21
N	586	586	586	592	595	604	605	602	601	600	598	593
Credit institutions												
Market cap in %	2.67	2.29	2.32	2.50	2.40	2.45	2.52	2.36	2.32	2.29	1.89	1.87
N	35	37	36	37	38	39	39	35	34	34	32	33
Investment banks												
Market cap in %	5.93	4.50	4.29	4.89	5.07	5.51	6.44	7.09	8.50	8.48	8.83	8.89
N	34	35	35	34	36	37	38	39	38	40	40	43
Financial firms												
Market cap in %	36.80	30.57	30.04	30.99	30.73	31.22	32.65	29.94	31.59	31.36	31.40	29.97
N	655	658	657	663	669	680	682	676	673	674	670	669
TBTF												
Commercial banks												
Market cap in %	45.07	40.77	43.66	42.75	42.08	40.83	40.40	40.94	41.77	42.30	42.67	40.60
N	16	16	16	16	16	16	16	16	16	16	15	15
Credit institutions												
Market cap in %	4.16	18.06	16.81	16.68	16.51	18.74	16.48	18.41	15.07	15.30	14.83	17.54
N	6	7	7	7	7	8	7	8	7	7	7	8
Investment banks												
Market cap in %	13.97	10.59	9.49	9.59	10.68	9.22	10.47	10.72	11.58	11.04	11.11	11.89
N	4	4	4	4	4	4	4	4	4	4	4	4
Financial firms												
Market cap in %	63.20	69.43	69.96	69.01	69.27	68.78	67.35	70.06	68.41	68.64	68.60	70.03
N	26	27	27	27	27	28	27	28	27	27	26	27

	2007 1Q	2Q	3Q	Q4	2008 1Q	2Q	3Q	4Q	2009 1Q	2Q	3Q	4Q
Non-TBTF												
Commercial banks												
Market cap in %	19.14	17.03	16.84	17.48	18.17	22.79	22.01	26.45	29.21	22.16	19.99	21.19
N	584	583	577	563	561	556	551	532	530	521	511	501
Credit institutions												
Market cap in %	1.76	1.81	1.72	1.31	1.06	1.12	1.02	0.92	0.85	0.96	0.87	0.88
N	34	36	37	36	35	35	36	33	33	33	32	29
Investment banks												
Market cap in %	9.45	10.39	11.83	14.73	13.66	14.47	12.79	12.68	14.90	13.91	13.13	13.10
N	47	45	50	52	53	54	53	53	57	56	56	55
Financial firms												
Market cap in %	30.34	29.24	30.40	33.52	32.89	38.39	35.83	40.04	44.95	37.03	33.99	35.16
N	665	664	664	651	649	645	640	618	620	610	599	585
TBTF												
Commercial banks												
Market cap in %	40.78	38.99	41.14	41.22	42.17	36.64	42.98	45.72	40.40	46.89	46.21	43.50
N	15	15	15	15	15	15	14	12	12	12	12	12
Credit institutions												
Market cap in %	16.80	19.02	18.05	13.04	14.10	13.24	11.64	7.50	5.09	5.58	12.83	12.16
N	8	9	9	9	10	9	9	8	8	8	7	8
Investment banks												
Market cap in %	12.08	12.75	10.42	12.22	10.83	11.74	9.55	6.74	9.56	10.50	6.97	9.17
N	4	4	4	4	4	4	3	3	2	2	1	2
Financial firms												
Market cap in %	69.66	70.76	69.60	66.48	67.11	61.61	64.17	59.96	55.05	62.97	66.01	64.84
N	27	28	28	28	29	28	26	23	22	22	20	22

Figure 6: Accounting and market leverage ratio development across commercial banks, credit institutions and investment banks. Accounting leverage ratio refers to the quotient of total liabilities and total assets reported in the financial statement at the end of each quarter. Market leverage ratio refers to the quotient of total liabilities and the sum of market value of equity and total liabilities. The first panel depicts the accounting leverage ratio development of Non-TBTF and TBTF banks across financial industry classes separately. In the second panel the respective market leverage ratios are plotted. The figures at the top of each panel refer to the aggregate leverage ratio development (financial firms), respectively.

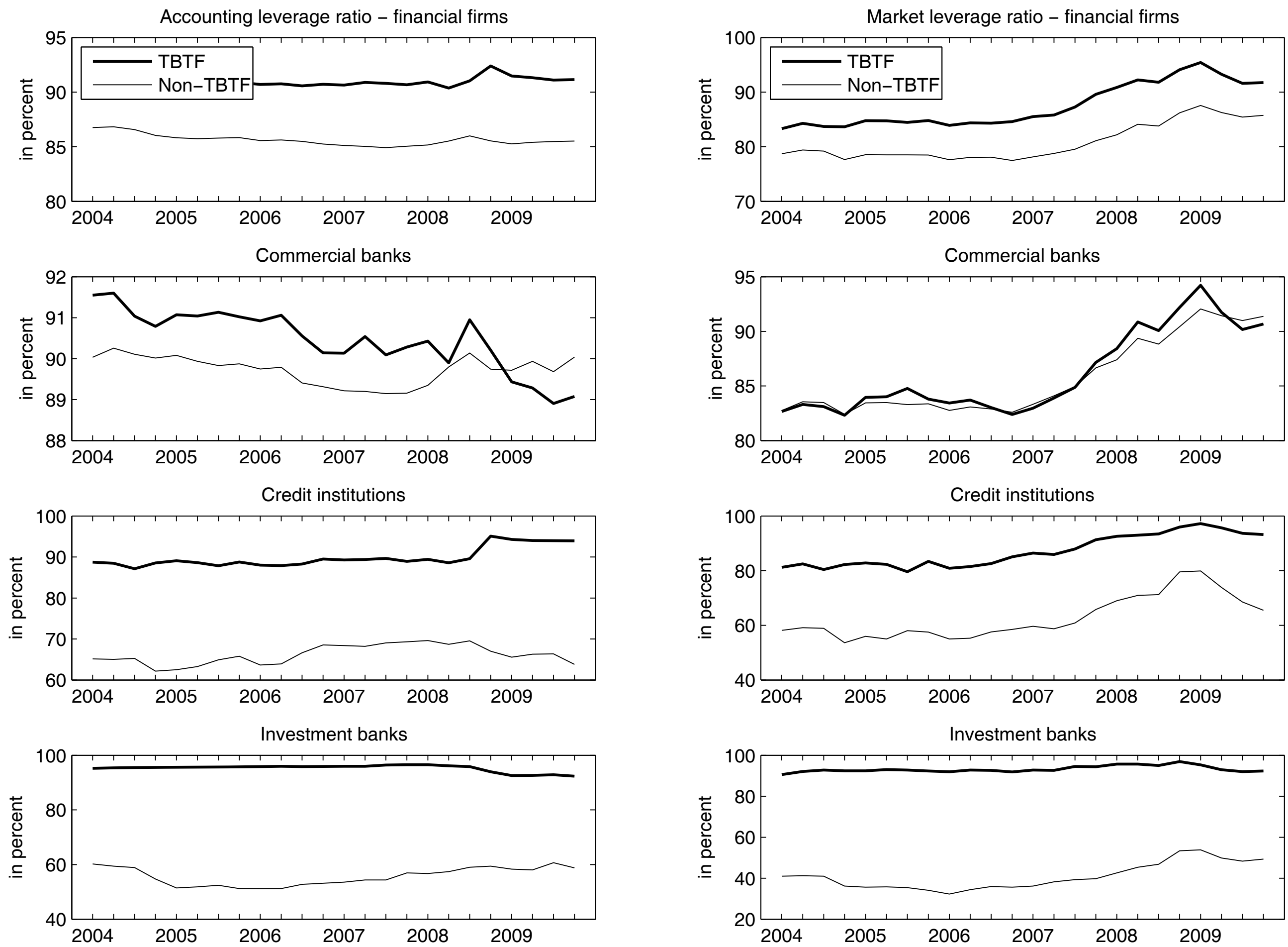


Table 10: Interest expenses across commercial banks, credit institutions and investment banks. This table provides the average interest and related expenses in percentages of the reported total liabilities at the end of each quarter. Interest expenses are quadrupled to obtain annualized expressions. N is the number of observations.

	2004 1Q	2Q	3Q	4Q	2005 1Q	2Q	3Q	4Q	2006 1Q	2Q	3Q	4Q
Non-TBTF												
Commercial banks												
Interest on debt in %	1.76	1.71	1.77	1.87	1.97	2.14	2.33	2.56	2.73	3.00	3.28	3.42
N	586	586	586	592	595	604	605	602	601	600	598	593
Credit institutions												
Interest on debt in %	5.17	5.49	4.76	5.74	5.25	5.55	4.71	4.54	4.94	5.03	5.08	5.59
N	35	37	36	37	38	39	39	35	34	34	32	33
Investment banks												
Interest on debt in %	1.85	1.89	2.34	1.96	2.01	1.86	2.21	2.16	2.15	2.28	2.50	2.83
N	34	35	35	34	36	37	38	39	38	40	40	43
Financial firms												
Interest on debt in %	1.95	1.93	1.96	2.09	2.16	2.32	2.46	2.64	2.81	3.06	3.32	3.49
N	655	658	657	663	669	680	682	676	673	674	670	669
TBTF												
Commercial banks												
Interest on debt in %	1.23	1.21	1.33	1.54	1.74	2.00	2.26	2.57	2.75	3.05	3.24	3.32
N	16	16	16	16	16	16	16	16	16	16	15	15
Credit institutions												
Interest on debt in %	1.95	2.07	2.19	2.40	2.51	2.91	3.03	3.45	3.49	3.87	4.10	4.25
N	6	7	7	7	7	8	7	8	7	7	7	8
Investment banks												
Interest on debt in %	1.95	1.97	2.27	2.67	2.93	3.37	3.71	4.20	4.40	4.73	5.14	5.11
N	4	4	4	4	4	4	4	4	4	4	4	4
Financial firms												
Interest on debt in %	1.50	1.54	1.69	1.93	2.12	2.46	2.67	3.06	3.18	3.51	3.77	3.86
N	26	27	27	27	27	28	27	28	27	27	26	27

	2007 1Q	2Q	3Q	Q4	2008 1Q	2Q	3Q	4Q	2009 1Q	2Q	3Q	4Q
Non-TBTF												
Commercial banks												
Interest on debt in %	3.44	3.52	3.58	3.48	3.16	2.75	2.66	2.54	2.26	2.11	1.96	1.78
N	584	583	577	563	561	556	551	532	530	521	511	501
Credit institutions												
Interest on debt in %	4.68	6.23	5.05	5.28	4.90	4.54	4.69	5.08	4.60	4.48	4.89	4.63
N	34	36	37	36	35	35	36	33	33	33	32	29
Investment banks												
Interest on debt in %	4.43	4.36	3.56	2.50	3.31	2.11	2.22	2.55	1.98	2.07	2.11	1.85
N	47	45	50	52	53	54	53	53	57	56	56	55
Financial firms												
Interest on debt in %	3.58	3.72	3.66	3.50	3.27	2.79	2.74	2.68	2.36	2.23	2.13	1.92
N	665	664	664	651	649	645	640	618	620	610	599	585
TBTF												
Commercial banks												
Interest on debt in %	3.25	3.27	3.33	3.17	2.62	2.07	1.92	1.59	1.34	1.20	1.10	0.99
N	15	15	15	15	15	15	14	12	12	12	12	12
Credit institutions												
Interest on debt in %	4.10	4.27	4.36	4.56	3.46	2.73	2.94	2.43	1.91	1.60	1.40	1.76
N	8	9	9	9	10	9	9	8	8	8	7	8
Investment banks												
Interest on debt in %	5.09	5.56	5.20	5.35	4.25	3.80	3.44	2.91	1.34	0.89	0.60	0.86
N	4	4	4	4	4	4	3	3	2	2	1	2
Financial firms												
Interest on debt in %	3.77	3.92	3.93	3.93	3.14	2.53	2.45	2.05	1.55	1.32	1.18	1.26
N	27	28	28	28	29	28	26	23	22	22	20	22

Table 11: Determinants of the refinancing cost level during the quiet (2004-2007) and stress period (2008-2009). This table presents the estimation results for the regression specified in equation (12). Associated Newey-West standard errors accounting for the *time-effect* with a lag of five appear in parentheses beneath. ***, ** and *, denote the statistical significance of the estimates at the 1%, 5% and 10% level, respectively.

	Quiet period 2004-2007	Stress period 2008-2009
Intercept	-25.81***	1.265
	(1.514)	(1.101)
log(Assets$_t$)	-0.0137**	-0.114***
	(0.00604)	(0.00792)
r_t	9.696***	1.255**
	(0.645)	(0.628)
r_t^2	-0.946***	-0.166*
	(0.0688)	(0.0959)
S&P 500 Return$_t$	6.391***	-0.146
	(0.265)	(0.147)
S&P 500 Return$_{t-1}$	4.067***	-1.484***
	(0.203)	(0.216)
Spread$_t$	0.914***	-0.188***
	(0.0370)	(0.0378)
Slope$_t$	-0.525***	-0.676***
	(0.0104)	(0.0606)
σ_{Et}	0.171***	0.0882***
	(0.0409)	(0.0286)
σ_{Et-1}	0.0444	0.0752**
	(0.0412)	(0.0312)
lev_{t-1}	3.610***	1.831***
	(0.188)	(0.288)
Dummy-TBTF$_t$	-0.0617*	-0.195***
	(0.0354)	(0.0565)
Tier-1-Ratio$_t$	-0.00500*	-0.0303***
	(0.00281)	(0.00420)
Observations	7,606	3,947
R^2	0.622	0.434

Table 12: Asset volatility (quarter) of financial firms. This table presents summary statistics for the asset volatility across financial firms subdivided into Non-TBTF and TBTF institutions quarterly from 2004-2009. The values are obtained by solving equations (8) and (9) using a calculated rolling 60-day annualized standard deviation of equity price changes (historical equity volatility), time to maturity of one year and market capitalization, total liabilities and dividend yield reported at the end of each quarter. All variables are winsorized at the 2nd and 98th percentile at each quarter across all banks (independent of TBTF or not). Mean represents the average value of the asset volatility for each quarter across Non-TBTF and TBTF financial firms, respectively. Std. Dev. captures the variation of this value. Median is the value separating the higher from the lower half of the respective sample. Minimum and Maximum values indicate the range of asset volatility values for each quarter across all banks. N is the number of observations. Mean diff is the difference between the mean value of Non-TBTF and TBTF financial firms.

	2004 1Q	2Q	3Q	4Q	2005 1Q	2Q	3Q	4Q	2006 1Q	2Q	3Q	4Q
Financial firms												
Non-TBTF												
Mean	6.1	6.8	5.9	0.058	5.6	6.3	5.1	5.4	5.2	6.3	5.8	5.2
Median	4.3	4.5	3.9	0.042	3.8	4.4	3.9	4.0	3.7	4.2	3.8	3.6
Std. Dev	6.3	7.8	6.5	0.055	5.8	6.0	4.2	0.052	5.3	7.1	6.1	5.1
Min	1.5	1.6	1.3	0.015	1.4	1.6	1.3	1.4	1.3	1.4	1.2	1.2
Max	45.4	52.2	45.0	42.6	43.8	39.9	29.4	38.1	33.6	42.6	38.9	30.5
N	630	634	633	642	646	656	657	651	646	646	645	643
TBTF												
Mean	3.2	3.9	6.0	3.4	3.1	3.1	2.6	3.0	2.7	4.2	2.9	2.4
Median	2.9	3.0	2.4	2.7	2.7	2.9	2.4	2.7	2.7	3.1	2.4	2.0
Std. Dev	1.5	3.2	11.0	1.6	1.5	1.3	1.1	1.2	1.1	5.6	1.5	1.2
Min	1.7	1.6	1.4	1.6	1.4	1.6	1.3	1.5	1.3	1.7	1.3	1.1
Max	8.2	16.8	42.8	7.0	7.0	6.8	5.8	6.4	6.4	31.7	8.2	6.6
N	25	25	25	22	24	24	24	25	26	27	25	27
Mean diff	2.9	2.9	-0.2	2.5	2.5	3.1	2.5	2.4	2.5	2.1	2.9	2.8

	2007 1Q	2Q	3Q	Q4	2008 1Q	2Q	3Q	4Q	2009 1Q	2Q	3Q	4Q
Financial firms												
Non-TBTF												
Mean	5.4	5.2	7.7	7.9	9.4	7.0	14.5	20.3	15.7	12.2	7.0	6.2
Median	3.6	3.4	5.3	5.6	6.2	4.4	10.1	12.7	9.6	7.0	4.5	3.9
Std. Dev	6.0	5.7	7.6	7.5	10.1	7.8	13.4	21.9	17.3	14.4	6.9	6.7
Min	1.2	1.0	1.6	1.7	2.0	1.5	2.4	2.5	1.9	1.5	1.0	1.0
Max	34.5	35.7	41.9	44.1	55.9	43.2	75.4	114.2	99.6	93.6	37.9	39.0
N	640	639	638	625	623	620	616	596	600	589	577	563
TBTF												
Mean	2.9	2.7	4.5	4.9	6.7	4.1	18.1	18.4	16.3	12.1	4.6	3.5
Median	2.7	2.5	4.7	4.5	5.6	3.9	18.2	15.5	13.1	11.5	4.5	2.8
Std. Dev	0.9	1.3	1.8	1.8	3.4	2.0	9.2	10.2	9.3	7.0	2.1	2.0
Min	1.5	1.3	1.7	2.6	2.7	1.5	5.7	8.8	5.1	2.0	1.6	1.3
Max	4.7	7.5	9.2	9.2	16.1	10.6	45.4	52.7	39.0	30.8	11.5	10.4
N	26	27	28	28	29	27	24	21	18	19	18	20
Mean diff	2.5	2.5	3.2	3.0	2.7	2.9	-3.6	1.8	-0.6	0.0	2.4	2.7

Table 13: Asset volatility (quarter) of commercial banks. This table presents summary statistics for the asset volatility across commercial banks subdivided into Non-TBTF and TBTF institutions quarterly from 2004-2009. The values are obtained by solving equations (8) and (9) using a calculated rolling 60-day annualized standard deviation of equity price changes (historical equity volatility), time to maturity of one year and market capitalization, total liabilities and dividend yield reported at the end of each quarter. All variables are winsorized at the 2nd and 98th percentile at each quarter across all banks (independent of TBTF or not). Mean represents the average value of the asset volatility for each quarter across Non-TBTF and TBTF financial firms, respectively. Std. Dev captures the variation of this value. Median is the value separating the higher from the lower half of the respective sample. Minimum and Maximum values indicate the range of asset volatility values for each quarter across all banks. N is the number of observations. Mean diff is the difference between the mean value of Non-TBTF and TBTF commercial banks.

	2004 1Q	2Q	3Q	4Q	2005 1Q	2Q	3Q	4Q	2006 1Q	2Q	3Q	4Q
Commercial banks												
Non-TBTF												
Mean	4.88	5.65	4.62	4.86	4.42	5.21	4.31	4.53	4.30	4.88	4.68	4.18
Median	4.07	4.33	3.76	3.98	3.66	4.28	3.66	3.78	3.57	3.93	3.69	3.40
Std. Dev.	3.27	6.04	4.11	3.45	3.17	3.85	2.65	3.38	3.43	4.35	4.02	3.28
Min	1.51	1.61	1.34	1.51	1.37	1.57	1.27	1.45	1.29	1.43	1.21	1.19
Max	32.26	52.18	43.42	41.00	34.07	37.62	25.84	38.13	33.55	41.90	36.85	28.86
N	569	571	568	578	579	590	592	589	587	581	584	575
TBTF												
Mean	3.00	3.15	5.14	2.84	2.63	2.93	2.44	2.86	2.71	3.09	2.65	2.35
Median	2.91	2.98	2.50	2.60	2.64	2.77	2.41	2.84	2.68	2.99	2.46	1.99
Std. Dev.	0.98	0.77	10.08	1.04	0.80	0.76	0.70	0.75	0.77	0.76	0.70	1.28
Min	1.75	1.90	1.37	1.57	1.41	1.74	1.32	1.51	1.62	1.99	1.92	1.55
Max	5.46	4.37	42.76	5.56	4.30	4.01	3.58	3.99	3.98	4.52	4.34	6.64
N	16	16	16	15	16	15	16	16	16	16	14	15
Mean diff	1.88	2.51	-0.52	2.02	1.79	2.28	1.87	1.67	1.59	1.79	2.03	1.83

	2007 1Q	2Q	3Q	Q4	2008 1Q	2Q	3Q	4Q	2009 1Q	2Q	3Q	4Q
Commercial banks												
Non-TBTF												
Mean	4.12	4.00	5.86	6.05	6.79	5.15	11.54	15.08	11.56	8.81	5.35	4.52
Median	3.38	3.23	4.91	5.19	5.67	4.16	9.08	11.33	8.67	6.41	4.24	3.62
Std. Dev.	3.62	3.48	4.13	4.04	5.07	4.18	8.96	14.36	11.19	9.42	4.56	3.94
Min	1.19	0.95	1.59	1.69	1.96	1.47	2.42	2.54	1.87	1.54	1.02	0.97
Max	34.47	32.88	38.06	33.50	44.35	38.32	60.95	114.20	99.62	77.79	37.94	39.00
N	570	569	563	548	547	543	535	522	518	507	502	489
TBTF												
Mean	3.02	2.57	5.21	5.19	7.27	4.42	22.54	17.22	19.97	13.73	4.58	3.58
Median	2.74	2.54	5.21	5.06	6.39	4.15	21.83	15.48	16.48	12.11	4.53	3.51
Std. Dev.	0.77	0.65	1.55	1.51	2.89	1.52	8.58	7.22	9.61	6.04	0.87	1.16
Min	2.19	1.61	3.04	3.53	4.85	2.36	12.07	10.58	10.40	6.19	3.09	2.32
Max	4.73	4.17	9.17	8.31	15.18	7.10	45.40	32.88	39.01	30.76	5.72	5.76
N	15	15	15	15	15	15	13	12	11	12	12	12
Mean diff	1.10	1.43	0.65	0.86	-0.48	0.72	-11.00	-2.14	-8.41	-4.92	0.77	0.94

Table 14: Asset volatility (quarter) development across commercial banks, credit institutions and investment banks. Asset vola refers to the average of calculated asset volatilities of each subclass. The values for each bank are obtained by solving equations (8) and (9) using a calculated rolling 60-day annualized standard deviation of equity price changes (historical equity volatility), time to maturity of one year and market capitalization, total liabilities and dividend yield reported at the end of each quarter. All variables are winsorized at the 2nd and 98th percentile at each quarter across all banks (independent of TBTF or not). N denotes the number of observations.

	2004 1Q	2Q	3Q	4Q	2005 1Q	2Q	3Q	4Q	2006 1Q	2Q	3Q	4Q
Non-TBTF												
Commercial banks												
Asset vola in %	4.88	5.65	4.62	4.86	4.42	5.21	4.31	4.53	4.30	4.88	4.68	4.18
N	569	571	568	578	579	590	592	589	587	581	584	575
Credit institutions												
Asset vola in %	16.97	17.73	15.41	14.13	15.04	13.69	10.63	11.54	12.16	14.60	12.25	11.59
N	32	34	34	35	36	34	34	30	30	33	28	32
Investment banks												
Asset vola in %	18.88	15.88	17.96	15.44	15.87	18.29	13.22	15.87	17.17	23.37	19.89	16.21
N	29	29	31	29	31	32	31	32	29	32	33	36
TBTF												
Commercial banks												
Asset vola in %	3.00	3.15	5.14	2.84	2.63	2.93	2.44	2.86	2.71	3.09	2.65	2.35
N	16	16	16	15	16	15	16	16	16	16	14	15
Credit institutions												
Asset vola in %	4.77	6.93	10.43	5.03	4.78	4.44	3.33	3.59	3.23	3.85	3.94	2.81
N	5	6	6	6	6	6	6	7	7	7	7	8
Investment banks												
Asset vola in %	2.23	1.76	1.81	1.55	1.63	1.65	1.26	1.66	1.74	9.47	1.72	1.74
N	4	3	3	1	2	3	2	2	3	4	4	4

	2007 1Q	2Q	3Q	Q4	2008 1Q	2Q	3Q	4Q	2009 1Q	2Q	3Q	4Q
Non-TBTF												
Commercial banks												
Asset vola in %	4.12	4.00	5.86	6.05	6.79	5.15	11.54	15.08	11.56	8.81	5.35	4.52
N	570	569	563	548	547	543	535	522	518	507	502	489
Credit institutions												
Asset vola in %	13.36	10.85	16.23	16.73	24.69	15.53	27.58	50.08	35.35	29.84	17.88	17.37
N	30	28	30	31	35	28	35	27	32	32	28	27
Investment banks												
Asset vola in %	18.40	18.05	25.37	24.15	30.69	23.29	39.38	60.71	45.92	34.81	17.86	17.04
N	40	42	45	46	41	49	46	47	50	50	47	47
TBTF												
Commercial banks												
Asset vola in %	3.02	2.57	5.21	5.19	7.27	4.42	22.54	17.22	19.97	13.73	4.58	3.58
N	15	15	15	15	15	15	13	12	11	12	12	12
Credit institutions												
Asset vola in %	3.30	3.58	4.35	5.32	6.67	4.40	13.66	15.67	10.42	11.26	5.10	3.72
N	7	8	9	9	10	8	8	6	5	5	5	6
Investment banks												
Asset vola in %	2.09	1.63	2.42	2.98	4.31	2.31	10.60	28.86	10.54	4.53	2.82	2.39
N	4	4	4	4	4	4	3	3	2	2	1	2

Table 15: Asset volatility (year) development across commercial banks, credit institutions and investment banks. Asset vola refers to the average of calculated asset volatilities of each subclass. The values for each bank are obtained by solving equations (8) and (9) using a calculated rolling 252-day annualized standard deviation of equity price changes (historical equity volatility), time to maturity of one year and market capitalization, total liabilities and dividend yield reported at the end of each quarter. All variables are winsorized at the 2nd and 98th percentile at each quarter across all banks (independent of TBTF or not). N denotes the number of observations and NaN stands for 'not a number' (the entries (NaN) in the TBTF investment bank subset are missing due to the winsorizing procedure).

	2004 1Q	2Q	3Q	4Q	2005 1Q	2Q	3Q	4Q	2006 1Q	2Q	3Q	4Q
Non-TBTF												
Commercial banks												
Asset vola in %	5.68	5.60	5.58	5.68	5.28	5.17	4.91	4.87	4.85	4.68	4.85	4.80
N	553	548	552	551	555	554	556	551	557	562	560	551
Credit institutions												
Asset vola in %	17.67	18.00	15.30	15.20	14.38	13.44	12.24	14.53	13.04	12.71	12.35	12.83
N	24	26	26	28	32	32	31	28	26	26	26	29
Investment banks												
Asset vola in %	20.25	17.47	17.84	18.27	15.51	15.11	14.79	15.97	18.04	19.34	19.38	18.81
N	26	25	26	27	28	27	28	28	29	30	27	30
TBTF												
Commercial banks												
Asset vola in %	3.32	3.07	3.65	4.40	3.95	3.78	3.16	2.77	2.92	2.84	3.84	3.80
N	16	16	16	16	16	16	15	16	15	16	15	15
Credit institutions												
Asset vola in %	11.80	5.70	6.89	6.75	6.16	5.73	4.22	3.61	3.67	3.70	3.78	3.44
N	5	6	6	6	6	6	6	7	6	6	6	7
Investment banks												
Asset vola in %	2.58	1.99	NaN	NaN	1.81	1.64	NaN	1.62	1.78	4.52	3.43	3.82
N	3	3	0	0	1	1	0	1	1	2	3	3

	2007 1Q	2Q	3Q	Q4	2008 1Q	2Q	3Q	4Q	2009 1Q	2Q	3Q	4Q
Non-TBTF												
Commercial banks												
Asset vola in %	4.52	4.22	4.43	4.51	5.18	4.79	6.80	7.81	8.13	9.97	9.80	7.27
N	541	539	541	530	529	526	520	514	512	503	490	483
Credit institutions												
Asset vola in %	13.76	12.78	14.16	14.93	16.06	19.38	18.99	25.06	27.19	36.78	40.00	31.42
N	27	26	28	28	30	32	33	29	30	30	30	27
Investment banks												
Asset vola in %	19.87	18.60	19.13	21.23	23.08	21.83	26.43	34.04	38.09	46.75	41.94	28.29
N	34	36	38	40	37	40	41	44	47	48	46	45
TBTF												
Commercial banks												
Asset vola in %	3.74	3.44	3.31	3.66	4.45	4.15	8.89	8.93	11.39	19.84	19.49	13.88
N	15	15	15	15	15	15	14	12	12	12	12	12
Credit institutions												
Asset vola in %	3.51	3.27	3.15	2.88	4.01	4.37	5.94	7.15	6.36	13.09	15.70	9.46
N	6	8	8	9	10	8	9	6	6	5	6	7
Investment banks												
Asset vola in %	3.04	1.79	1.69	2.17	2.33	2.67	4.21	6.11	10.11	14.34	10.35	5.68
N	4	4	4	4	4	4	3	3	2	2	1	2

Table 16: Absolute guarantee values for TBTF financial firms across subclasses and asset volatility specifications. Guarantee values are reported in millions and obtained by using the simulation approach described in Subsection 3.4 with an assumed debt maturity of one year, where the panel on the top (at the bottom) provides the results for a 60 (252)-day historical equity volatility.

With asset vola - quarter year	2004 1Q	2Q	3Q	4Q	2005 1Q	2Q	3Q	4Q	2006 1Q	2Q	3Q	4Q
Financial firms	3.63	4387.91	289333.29	25044.51	8.94	46.49	1.45	87.83	28.20	113291.12	135093.53	710.50
Commercial banks	0.30	9.07	264826.47	24973.21	0.00	1.31	0.00	0.30	0.04	6.00	133359.14	1.62
in % of financial firms	8.19	0.21	91.53	99.72	0.00	2.83	0.00	0.34	0.13	0.01	98.72	0.23
Credit institutions	3.00	4376.45	24495.48	71.20	7.97	11.41	0.56	70.97	5.96	86.02	289.04	31.49
in % of financial firms	82.58	99.74	8.47	0.28	89.22	24.54	38.38	80.80	21.15	0.08	0.21	4.43
Investment banks	0.33	2.38	11.33	0.10	0.96	33.77	0.89	16.57	22.20	113199.10	1445.35	677.39
in % of financial firms	9.23	0.05	0.00	0.00	10.78	72.63	61.62	18.86	78.73	99.92	1.07	95.34
	2007 1Q	2Q	3Q	Q4	2008 1Q	2Q	3Q	4Q	2009 1Q	2Q	3Q	4Q
Financial firms	2811.54	3274.48	30679.57	40498.25	80863.73	10155.59	850351.13	665307.12	626359.04	157515.55	4975.62	23458.13
Commercial banks	9.28	0.12	1631.17	2496.24	19906.79	3706.92	673418.74	244777.18	538910.01	128018.87	670.27	60.42
in % of financial firms	0.33	0.00	5.32	6.16	24.62	36.50	79.19	36.79	86.04	81.27	13.47	0.26
Credit institutions	503.65	1820.56	10617.30	29716.16	30498.51	2480.01	91797.52	130329.44	56830.16	28573.82	4305.35	23396.56
in % of financial firms	17.91	55.60	34.61	73.38	37.72	24.42	10.80	19.59	9.07	18.14	86.53	99.74
Investment banks	2298.60	1453.80	18431.10	8285.86	30458.43	3968.66	85134.88	290200.50	30618.86	922.87	0.00	1.14
in % of financial firms	81.76	44.40	60.08	20.46	37.67	39.08	10.01	43.62	4.89	0.59	0.00	0.00
With asset vola - one year	2004 1Q	2Q	3Q	4Q	2005 1Q	2Q	3Q	4Q	2006 1Q	2Q	3Q	4Q
Financial firms	9261.05	680.75	20635.23	22090.05	22373.70	22017.64	1879.95	309.96	30.61	12491.13	24571.97	26537.05
Commercial banks	0.90	0.48	16075.85	18144.05	18505.71	19391.81	1860.63	0.07	0.30	0.27	10903.83	10513.80
in % of financial firms	0.01	0.07	77.90	82.14	82.71	88.07	98.97	0.02	0.99	0.00	44.38	39.62
Credit institutions	9254.92	679.17	4556.78	3943.18	3864.05	2615.63	11.59	291.98	5.24	7.26	74.93	186.40
in % of financial firms	99.93	99.77	22.08	17.85	17.27	11.88	0.62	94.20	17.11	0.06	0.30	0.70
Investment banks	5.23	1.11	2.60	2.82	3.94	10.19	7.73	17.91	25.07	12483.59	13593.21	15836.84
in % of financial firms	0.06	0.16	0.01	0.01	0.02	0.05	0.41	5.78	81.90	99.94	55.32	59.68
	2007 1Q	2Q	3Q	Q4	2008 1Q	2Q	3Q	4Q	2009 1Q	2Q	3Q	4Q
Financial firms	27081.48	14264.01	11529.00	7887.71	17066.59	12090.35	121942.90	126974	183086.90	378819.25	399620.93	191352.1
Commercial banks	10021.61	10914.46	40.42	212.62	1445.94	1615.43	72961.19	49806.12	121412.70	306415.44	225797.75	109852.7
in % of financial firms	37.01	76.52	0.35	2.70	8.47	13.36	59.83	39.23	66.31	80.89	56.50	57.41
Credit institutions	285.97	1066.91	2945.78	4211.58	9753.46	5342.36	38586.83	44805.27	32727.75	28992.94	169750.61	79523.34
in % of financial firms	1.06	7.48	25.55	53.39	57.15	44.19	31.64	35.29	17.88	7.65	42.48	41.56
Investment banks	16773.89	2282.63	8542.80	3463.51	5867.18	5132.56	10394.89	32362.62	28946.40	43410.86	4072.57	1976.06
in % of financial firms	61.94	16.00	74.10	43.91	34.38	42.45	8.52	25.49	15.81	11.46	1.02	1.03

Table 17: Relative guarantee values across commercial banks, credit institutions and investment banks. This table provides the average relative guarantee values for each subclass and all financial firms. Rel. guarantee value refers to the ratio of guarantee value to initial total assets. The guarantee values for each bank are obtained by using the simulation approach described in Subsection 3.4 with an assumed debt maturity of one year and a 60-day historical equity volatility. All variables are winsorized at the 2nd and 98th percentile at each quarter across all banks (independent of TBTF or not). N denotes the number of observations.

	2004 1Q	2Q	3Q	4Q	2005 1Q	2Q	3Q	4Q	2006 1Q	2Q	3Q	4Q
Non-TBTF												
Commercial banks												
Rel. guarantee in %	0.47	0.85	0.43	0.30	0.15	0.44	0.11	0.14	0.12	0.36	0.26	0.14
N	566	566	564	573	574	584	586	584	581	579	579	572
Credit institutions												
Rel. guarantee in %	2.85	3.91	2.61	1.58	1.96	2.16	0.66	0.52	0.66	0.52	0.82	0.58
N	31	36	35	34	37	36	34	30	31	33	29	32
Investment banks												
Rel. guarantee in %	2.99	2.70	2.77	1.22	0.65	1.18	0.30	0.45	0.89	2.73	1.82	0.69
N	32	30	32	31	32	32	34	34	33	34	37	39
Financial firms												
Rel. guarantee in %	0.56	0.80	0.55	0.30	0.17	0.44	0.11	0.13	0.13	0.38	0.27	0.14
TBTF												
Commercial banks												
Rel. guarantee in %	0.00	0.00	1.64	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	16	16	16	15	16	16	16	16	16	16	14	15
Credit institutions												
Rel. guarantee in %	0.00	0.59	3.22	0.01	0.00	0.00	0.00	0.00	0.00	0.05	0.04	0.01
N	6	7	7	7	7	8	7	8	7	7	7	8
Investment banks												
Rel. guarantee in %	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.39	0.08	0.03
N	4	4	4	4	4	4	4	4	4	4	4	4
Financial firms												
Rel. guarantee in %	0.00	0.14	1.66	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.02	0.01

	2007 1Q	2Q	3Q	Q4	2008 1Q	2Q	3Q	4Q	2009 1Q	2Q	3Q	4Q
Non-TBTF												
Commercial banks												
Rel. guarantee in %	0.13	0.16	1.01	0.79	1.45	0.92	6.96	15.23	12.97	8.64	2.59	1.55
N	567	561	561	546	541	537	531	512	506	499	490	482
Credit institutions												
Rel. guarantee in %	1.55	1.37	4.80	1.81	2.47	2.13	7.25	62.32	48.97	20.21	3.66	1.27
N	30	35	32	35	33	32	31	31	33	32	32	28
Investment banks												
Rel. guarantee in %	0.85	0.51	3.67	0.13	1.26	0.40	5.70	29.55	13.62	8.50	1.50	0.29
N	42	42	45	46	49	51	52	51	57	55	53	51
Financial firms												
Rel. guarantee in %	0.16	0.20	1.06	0.68	1.30	0.81	6.04	15.46	12.72	8.08	2.32	1.29
TBTF												
Commercial banks												
Rel. guarantee in %	0.00	0.00	0.05	0.07	0.60	0.16	9.83	4.81	10.46	2.83	0.03	0.00
N	15	15	15	13	15	14	14	12	12	12	12	12
Credit institutions												
Rel. guarantee in %	0.03	0.08	0.53	0.95	1.37	0.33	4.15	4.67	1.99	1.52	0.07	0.35
N	8	9	9	9	10	9	9	8	8	8	7	8
Investment banks												
Rel. guarantee in %	0.08	0.06	0.60	0.24	0.91	0.15	3.29	15.32	2.36	0.07	0.00	0.00
N	4	4	4	4	4	4	3	3	2	2	1	2
Financial firms												
Rel. guarantee in %	0.02	0.03	0.25	0.32	0.76	0.16	6.29	5.66	6.01	1.88	0.04	0.13

Table 18: Relative guarantee values across financial firms with a target liability to asset ratio of 70%. This table provides the average relative guarantee values for each subclass and all financial firms. Rel. guarantee value refers to the ratio of guarantee value to initial total assets. The guarantee values for each bank are obtained by using the simulation approach described in Subsection 3.4 with an assumed debt maturity of one year and a 60-day historical equity volatility where we reduce the target liability to asset ratio from 92% to 70%. All variables are winsorized at the 2nd and 98th percentile at each quarter across all banks (independent of TBTF or not). *N* denotes the number of observations.

	2004 1Q	2Q	3Q	4Q	2005 1Q	2Q	3Q	4Q	2006 1Q	2Q	3Q	4Q
Non-TBTF												
Commercial banks												
Rel guarantee in %	0.06	0.18	0.12	0.03	0.02	0.05	0.00	0.00	0.01	0.04	0.02	0.01
N	566	563	564	572	574	583	585	583	580	576	577	571
Credit institutions												
Rel guarantee in %	0.48	0.71	0.27	0.16	0.12	0.28	0.03	0.03	0.02	0.02	0.06	0.03
N	33	37	35	35	37	37	35	30	31	33	29	32
Investment banks												
Rel guarantee in %	0.49	0.68	0.92	0.13	0.05	0.21	0.02	0.03	0.06	0.72	0.18	0.03
N	30	32	32	31	32	32	34	35	34	38	39	40
Financial firms												
Rel guarantee in %	0.10	0.24	0.17	0.04	0.03	0.07	0.01	0.01	0.01	0.08	0.03	0.01
TBTF												
Commercial banks												
Rel guarantee in %	0.00	0.00	1.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	16	16	16	15	16	16	16	16	16	16	14	15
Credit institutions												
Rel guarantee in %	0.00	0.22	2.34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	6	7	7	7	7	8	7	8	7	7	7	8
Investment banks												
Rel guarantee in %	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	4	4	4	4	4	4	4	4	4	3	4	4
Financial firms												
Rel guarantee in %	0.00	0.06	1.34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	2007 1Q	2Q	3Q	Q4	2008 1Q	2Q	3Q	4Q	2009 1Q	2Q	3Q	4Q
Non-TBTF												
Commercial banks												
Rel guarantee in %	0.00	0.01	0.09	0.07	0.18	0.06	2.53	6.35	5.99	3.98	0.53	0.19
N	565	561	558	539	539	532	531	513	510	497	489	479
Credit institutions												
Rel guarantee in %	0.05	0.15	0.69	0.25	0.33	0.48	1.74	32.78	21.53	8.34	0.43	0.14
N	29	33	31	35	33	33	32	32	33	33	31	28
Investment banks												
Rel guarantee in %	0.08	0.09	0.58	0.00	0.05	0.02	0.74	9.96	3.53	4.02	0.13	0.01
N	45	44	49	51	51	54	51	51	56	56	55	54
Financial firms	0.01	0.02	0.16	0.08	0.18	0.08	2.34	8.08	6.61	4.23	0.48	0.17
Rel guarantee in %												
TBTF												
Commercial banks	0.00	0.00	0.00	0.00	0.18	0.00	6.94	2.22	6.71	1.13	0.00	0.00
Rel guarantee in %	15	15	15	15	15	15	14	12	12	12	12	12
N												
Credit institutions	0.00	0.00	0.06	0.06	0.21	0.01	1.32	2.52	0.62	0.31	0.00	0.00
Rel guarantee in %	8	9	9	9	10	9	9	6	5	8	7	8
N												
Investment banks	0.00	0.00	0.04	0.00	0.09	0.00	1.36	11.65	0.67	0.00	0.00	0.00
Rel guarantee in %	4	4	4	4	4	4	3	3	2	2	1	2
N												
Financial firms												
Rel guarantee in %	0.00	0.00	0.02	0.02	0.18	0.00	4.36	3.66	4.47	0.73	0.00	0.00

Figure 7: Relative guarantee values (year) across commercial banks, credit institutions and investment banks. First panel: development of relative guarantee values of financial firms and its composition across all subclasses. Second panel: difference in the respective relative guarantee levels of Non-TBTF and TBTF banks. Relative guarantee value refers to the ratio of guarantee value to initial total assets. The guarantee values for each bank are obtained by using the simulation approach described in Subsection 3.4 with an assumed debt maturity of one year and a 252-day historical equity volatility. All variables are winsorized at the 2nd and 98th percentile at each quarter across all banks (independent of TBTF or not).

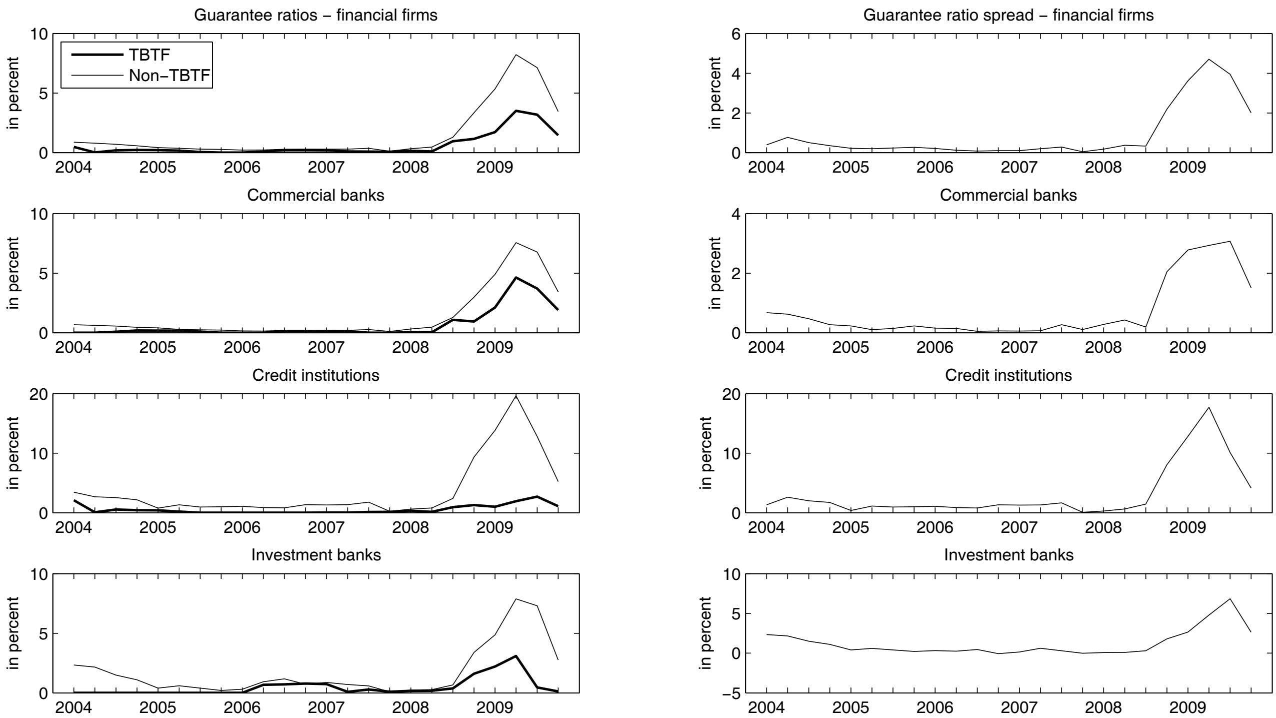


Table 19: Absolute guarantee values for TBTF financial firms across subclasses with a target liability to asset ratio of 70%. Guarantee values are reported in millions and obtained by using the simulation approach described in Subsection 3.4 with an assumed debt maturity of one year and a 60-day historical equity volatility where we reduce the target liability to asset ratio from 92% to 70%. NaN stands for 'not a number', the entries (NaN) are missing because we do not divide by zero, the respective guarantee value of all financial firms.

Absolute values	2004 1Q	2Q	3Q	4Q	2005 1Q	2Q	3Q	4Q	2006 1Q	2Q	3Q	4Q
Financial firms	0.00	1787.10	235786.05	20296.08	0.00	0.01	0.00	0.00	0.00	94171.76	110960.43	0.00
Commercial banks	0.00	0.00	216364.60	20295.64	0.00	0.00	0.00	0.00	0.00	0.00	110958.47	0.00
in % of financial firms	NaN	0.00	0.92	1.00	NaN	0.00	NaN	NaN	NaN	0.00	1.00	NaN
Credit institutions	0.00	1787.10	19421.46	0.44	0.00	0.01	0.00	0.00	0.00	2.99	0.06	0.00
in % of financial firms	NaN	1.00	0.08	0.00	NaN	1.00	NaN	NaN	NaN	0.00	0.00	NaN
Investment banks	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	94168.76	1.89	0.00
in % of financial firms	NaN	0.00	0.00	0.00	NaN	0.00	NaN	NaN	NaN	1.00	0.00	NaN

	2007 1Q	2Q	3Q	Q4	2008 1Q	2Q	3Q	4Q	2009 1Q	2Q	3Q	4Q
Financial firms	1.05	25.35	2163.26	1675.76	9727.23	66.67	587753.13	370725.21	342709.85	45467.78	8.74	0.68
Commercial banks	0.00	0.00	8.62	6.76	4442.19	60.30	537475.20	101598.76	329029.87	42211.82	0.58	0.03
in % of financial firms	0.00	0.00	0.00	0.00	0.46	0.90	0.91	0.27	0.96	0.93	0.07	0.04
Credit institutions	0.01	25.35	1076.05	1668.37	2319.32	5.37	14003.91	37204.79	4923.26	3254.27	8.16	0.65
in % of financial firms	0.01	1.00	0.50	1.00	0.24	0.08	0.02	0.10	0.01	0.07	0.93	0.96
Investment banks	1.04	0.00	1078.59	0.64	2965.72	1.01	36274.01	231921.65	8756.73	1.70	0.00	0.00
in % of financial firms	0.99	0.00	0.50	0.00	0.30	0.02	0.06	0.63	0.03	0.00	0.00	0.00

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Losses from time-structured supply chain disruptions

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This paper was presented at:

- 22^{nd} International Conference of the Production and Operations Management Society (April 2011)
- 2^{nd} Annual Conference of the European Decision Science Institute (June 2011)
- the research seminar at the Hong Kong City University (July 2011)

Abstract

A model for the quantification of business interruption risk in a supply chain network is proposed. To calculate the loss distribution induced by supply chain disruptions for a focal firm we apply a bottom-up modeling approach. On the firm level we model production disruptions of various hazard events in reduced form. We incorporate the network structure explicitly and define the loss propagation between the firms. Via Monte Carlo simulation we analyze the effects of different model specifications and network structures on the loss distribution of the focal firm. Our methodology and findings enable more informed and transparent decisions for supply chain design.

1 Introduction

As a result of fiercer competition, growing customer needs, accelerated globalization of markets and rapidly developing technology, almost all industries have experienced massive pressure to make intrafirm and interfirm business processes more efficient and/or more responsive. Firms outsource manufacturing and research and development (R&D) activities, source in low-cost countries, reduce inventories and slack, streamline the supply base and collaborate more intensively with other members of the supply chain. For instance, as part of a globalized value creation, Lenovo Group, Ltd. has manufacturing plants and fulfillment operations centers in China, India, Mexico and Poland; its R&D centers are located in the USA, China and Japan. The company sources parts from suppliers located all over the world, all of which are connected through information channels, flows of funds and production flows that contribute to the overall profits of the group. Naturally, the potential cost reductions and improved operational efficiencies achieved through these management decisions come at a cost: supply chain networks (SCNs) are becoming large and densely interconnected, which increases the production-inherent complexity and uncertainty. Therefore, predictions regarding output losses from production breakdowns in the supply chain are difficult to make due to the interaction of firms and the dispersion of losses through the network. Last year the erupted ash of Iceland's volcano Eyjafjallajokull disrupted air transport of passengers but also of goods across Europe, which according to European Commission could cost up to \$3.3 bn.[1] Recent disastrous events in Japan have demonstrated the vulnerability and interconnectedness of the world's supply chains. Lenovo experienced issues with the supply of its second- and third-tier parts, such as small controllers used in laptops, due to these events. However, the company's supply chain team managed to find additional supplies to avoid production disruptions (Stahl and Prince (2011)). In the car industry shortages of parts delivered from Japan, forced General Motors to halt production at its pickup plant in Shreveport, USA. Opel called a 24-hour production stop at its plant in Saragossa, Spain, due to the lack of an electronic item. Toyota Motor Corp. reported a production loss of 260'000 cars in Japan from March 14 to April 8 2011 alone (Shino (2011)).

This paper introduces a conceptual framework for the field of disruption risk management in SCNs. We propose a generic model for calculating the loss distribution of an appointed (in the following 'focal') firm due to time-structured disruptions in a given network. For each firm in the network, we allow a variety of hazard events which can be idiosyncratic (e.g., machine malfunction) or systematic and affecting more than one firm (e.g., natural catastrophes). We describe the interaction of different hazard events on the firm level and account for the time required for resolving the disruption using renewal-reward processes. The interaction and dispersion of disruption losses across firms are obtained by incorporating the network topology explicitly. The latter modeling aspect allows us to reproduce contagious effects; i.e., idiosyncratic disruptions may affect other firms in the SCN by propagating through existing linkages among firms. By

[1]See European Commission, The impact of the Volcanic Ash Cloud Crisis on the Air Transport Industry, SEC(2010) 533, 27th April 2010.

incorporating systematic hazard events and network topology (contagion), we cover two fundamental aspects of interdependency among firms in SCNs that are essential for estimating the loss distribution from disruptions in each node in the network. We implement the model and investigate some idealized examples via a Monte Carlo (MC) simulation. First, we show the effects of different possible model specifications on expected losses and other distributional measures. Then, we analyze typical and relevant settings for supply chain management. In particular, we are interested in the impact and direction of certain diversification strategies (e.g., relocation of suppliers). In collaboration with a large insurance company, we specify the data requirements necessary to calculate the losses with the proposed model.

Deleris, Elkins, and Paté-Cornell (2004) and Deleris and Erhun (2005), in one of the initial quantitative approaches to modeling hazard event exposures in SCNs, concentrated on the implementation and simulation of a single hazard event. We adapt parts of this general approach but extend it in several ways. First, we do not limit ourselves to disruptions caused by fire, but allow a broad set of hazard events. This necessitates that we also specify the mechanics as the interaction of hazard events not only on the firm-level but also across firms. Second, we focus exclusively on losses from supply chain disruptions. Therefore, we obtain predictions on losses from different hazard categories and provide managerial implications. Third, we introduce definitions and theoretical concepts as stochastic processes in an accurate and complete way. The vast majority of contributions and deduced managerial recommendations in the literature are of normative nature, anecdotal or case study-based. For instance, a firm that seeks to take advantage of economies of scale in its inbound supply chain by pursuing a single sourcing strategy concurrently might suffer from an increased negative impact of supply side disruptions. The premise that diversification reduces risk seems to be intuitive when we think of portfolio theory. However, it is insufficient in the context of SCN's substantiated quantification. To our knowledge, the majority of previous research has focused on a simple setup of buyer-supplier relationship, thus neglecting the structure of the SCN (as highlighted by Choi and Wu (2009)). Ultimately, it is not obvious whether the evolving network structure exacerbates or mitigates the effects of those hazard events on the production process and profitability of the firm. On the one hand, a diversified supplier structure-e.g., across countries or more generally across different hazard events-can be helpful to dampen the impact of single production disruptions. On the other hand, the linkages among firms induce contagion effects-i.e., single disruptions propagate, and therefore the consequences may be more pronounced and harmful. Thus, a better understanding of the described mechanics and how supply chain design affects the inherent risk exposure is very important.

The paper is organized as follows: Section 2 discusses the existing literature. The formal model is then introduced and described in Section 3. In Section 4 we implement the model and analyze some stylized examples. Section 5 elaborates on the implications for managerial practice. Finally, we give an overview of the relevant findings and draw conclusions.

2 Literature review

In recent years a growing number of researchers and practitioners have put supply chain risks on their agendas, motivated in particular by catastrophic events that have disrupted economies and supply chains around the globe. Banks (2006) provides a comprehensive analysis of catastrophic risk management from the perspective of the financial industry. However, it is not only prominent 'macro' events that lead to costly supply chain disruptions. A substantial body of recent literature reports on events at the supply chain level that resulted in serious problems for the involved firms (e.g., Norrman and Jansson (2004); Kleindorfer and Saad (2005)). Numerous proposals for best practices and guidelines for risk mitigation and business continuity planning that aim to create secure, robust, and/or resilient supply chains have been published recently (e.g., Chopra and Sodhi (2004); Tang (2006); Craighead, Blackhurst, Rungtusanatham, and Handfield (2007)). The influence of disruptions on the performance of the supply chain is investigated, for instance, by Chen and Yano (2010). Reactive strategies for supply chain disruption management are studied by Shao and Dong (2010). Their findings support the application of reactive strategies to supply chain disruptions by supply chain managers, and provide guidance to minimize the loss of profits and customers during the disruption. The negative effects of supply chain disruptions on operational performance are investigated by Hendricks and Singhal (2005). They find that firms which experience supply chain disruptions report on average 6.92% lower sales growth, 10.66% higher cost and 13.88% higher inventories. Moreover, during the two-year time period after the disruption announcement, these indicators do not improve. Mitigation and contingency strategies are thoroughly discussed by Tomlin (2006). With a discrete Markov process to model supply chain disruptions, the author compares the effectiveness of different risk mitigation strategies in a simple setup with one focal firm and two suppliers. Depending on the length of the disruption, mitigation, rather than contingent rerouting, tends to be optimal if disruptions are rare.

More relevant for our work is the literature concerning SCNs and their analysis as complex systems. The literature draws on different areas of economic research. First, we use basic concepts and definitions for describing networks. Jackson (2010) gives a very extensive overview of the economic and social network literature. Here, we are not primarily interested in the formation of networks, but in the consequences and managerial implications of given SCNs. Cossin and Schellhorn (2007) present a model of credit risk in a network economy. Based on the example of the U.S. automotive industry, they develop a structural model of cash-flow risk that causes interdependencies between firms. In the context of SCN dynamics, Mizgier, Wagner, and Holyst (2012) examine how companies default. Their paper is based on the agent-based supply chain model proposed by Weisbuch and Battiston (2007) and further studied by Battiston, Gatto, Gallegati, Greenwald, and Stiglitz (2007) in the context of bankruptcy propagation and credit relations. The authors use an agent-based modeling approach to describe the interaction among heterogeneous agents. The main goal of this technique is to gain insights on how the behavior of the system arises from interactions between autonomous agents. Another focus in this research area is the optimal design of SCNs in uncertain economic environments. Klibi, Martel, and Guitouni (2010) present a review of optimization models proposed in the literature and provide the foundations for a robust SCN design methodology. They highlight the need for new SCN multi-hazard modeling techniques necessary for efficient decision making under uncertain conditions.

Another trend in the literature is the calculation of problem-inherent losses for network structures. Nagurney and Qiang (2009) present a comprehensive study of the network approach to deal with interdependencies and uncertainties in economic and social networks. In the finance context the work of Egloff, Leippold, and Vanini (2007) incorporate interfirm relations of obligors in a structural credit risk portfolio model explicitly. They show that the portfolio loss distribution exhibits significantly higher risk compared to conventional models. Operational activities that are essential to a bank's business model (business continuity management) are modeled and studied in Leippold and Vanini (2005). Instead of incorporating network topologies explicitly, another common approach to capture default dependencies in credit portfolios is to use copula functions (Li (2000)). Wagner, Bode, and Koziol (2009) apply this approach to supplier networks and illustrate the significant impact of default correlation in a supplier portfolio. In a simple setup of a network with one stage of suppliers, Babich, Burnetas, and Ritchken (2007) recommend that once the suppliers are chosen, reducing their correlation will be advantageous. For example, they may attempt to sell to different customers, use different production technologies and/or procure from different raw material sources in order to reduce exposure to common country-specific risks or common catastrophic events.

Deleris, Elkins, and Paté-Cornell (2004) and Deleris and Erhun (2005) explicitly study supplier networks where disruptions in the production process are modeled in reduced form. Their main idea is to introduce two separate models, a hazard model for describing the disruptions on the firm level and an operations model that incorporates the network topology by characterizing the interaction between the firms in the SCN. For the integration of these building blocks, they employ Generalized Semi-Markov Processes (GSMP), on which we give more details later in the paper. The estimation of the loss distribution is then conducted via a Monte-Carlo (MC) simulation. The former paper focuses on disruptions caused only by fires and hence their analysis does not reflect the actual risk of each firm in the network, where various types of risk exist. In the latter work the set of hazard events is extended and the risk assessment (loss of volume) is based on a flow model of the network. Both papers give a short overview of the model and state the flexibility and generalizability of this approach using a simple example of an actual supply chain but do not present any managerial implications.

3 Modeling approach

In this part we introduce the terminology and formal description regarding the SCN under consideration, disruption risks, associated severities and the interaction of all these elements.

3.1 Supply chain network structure

A SCN is a complex system of interconnected firms consisting of suppliers, focal firms, distributors and customers. The loss distribution arising from disruptions in the focal firms' supply chain is the subject of our investigation. The general network structure is depicted in Figure 1. We can imagine a globally active company like Procter & Gamble (P & G) with suppliers

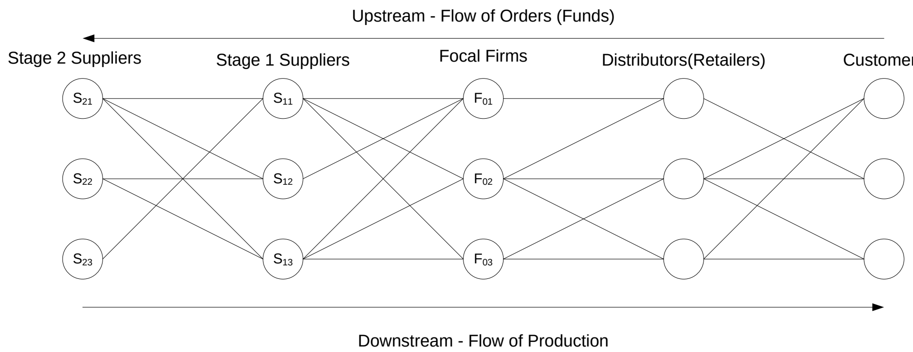

Figure 1: The supply chain network structure

located in different parts of the world. In our example P & G will be the focal firm and our aim would be to map the structure between P & G and its suppliers. Since P & G is operating in a complex market with many suppliers, who are able to deliver the same goods, P & G can choose among them (single vs. multi-sourcing strategy) and negotiate different contracts. Those contracts specify the amount of parts delivered, time, quality, cost and other factors that influence the type and intensity of the buyer-supplier relationship. P & G's suppliers can also deliver to other companies in the market, which makes the supply chain network highly complex and difficult to study. The chain of suppliers ends up at the tier of the raw material suppliers. The flows across the supply chain network can occur in two directions (we exclude feedback loops):

- *upstream*: from the customer to the raw material suppliers (flow of information or funds) and
- *downstream*: from raw material suppliers to the customer (flow of production),

where we focus on the downstream case. Moreover, we can distinguish between value-adding and non-value adding units. By value adding units we understand nodes in the network where activities like operations (production), inbound/outbound logistics, marketing and sales (demand) and services take place, as opposite to the non-value adding units like warehouses.

Our SCN $\mathcal{F} \cup \mathcal{S} = \{F_{01}, F_{02}, \ldots\} \cup \{S_{11}, S_{12}, \ldots, S_{21}, \ldots\}$ consists of $|\mathcal{F} \cup \mathcal{S}| = N$ agents divided into focal firms $\mathcal{F}$ and suppliers $\mathcal{S}$ on different tiers denoted by S_{kl} where k indicates the tier and l the number of the supplier on the specific tier. In the following we only consider one focal firm F_{01}. The relationships between the firms are described by a *directed graph* associated with the adjacency $\Xi = (\xi_{ij})_{i,j=1,\ldots,N}$. The entry ξ_{ij} represents the purchasing volume sourced by firm j from firm i, expressed as the percentage of the total order per time unit. It can also be interpreted as the exposure of j to i, because if supplier i suffers a production disruption the ordered products cannot be delivered and the buying firm j will be negatively affected. Note that the first row corresponds to the volume the focal firm purchases from its suppliers. The network structure is assumed to be static. The matrix collects the direct business dependencies reporting the maximum exposure of a firm (business volume) if a disruption in one of the neighboring firms occurs. The impact of disruptions on stages farther in the network is not considered.

In the following example we introduce a simple fundamental network structure which accompanies us through the paper to illustrate different concepts of the modeling approach.

Example 3.1. *We study a SCN with six agents: one focal firm F_{01} with three suppliers in the first stage S_{11}, S_{12}, S_{13} and two suppliers' suppliers S_{21}, S_{22} (second stage). The network structure is depicted in Figure 2. The matrix $\boldsymbol{\Xi}$ is given by*

$$\boldsymbol{\Xi} = \begin{pmatrix} 0 & 0 & 1 & 0.8 & 0.6 & 0 \\ 0 & 0 & 0 & 0.2 & 0.4 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.7 \\ 0 & 0 & 0 & 0 & 0 & 0.2 \\ 0 & 0 & 0 & 0 & 0 & 0.1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} . \tag{1}$$

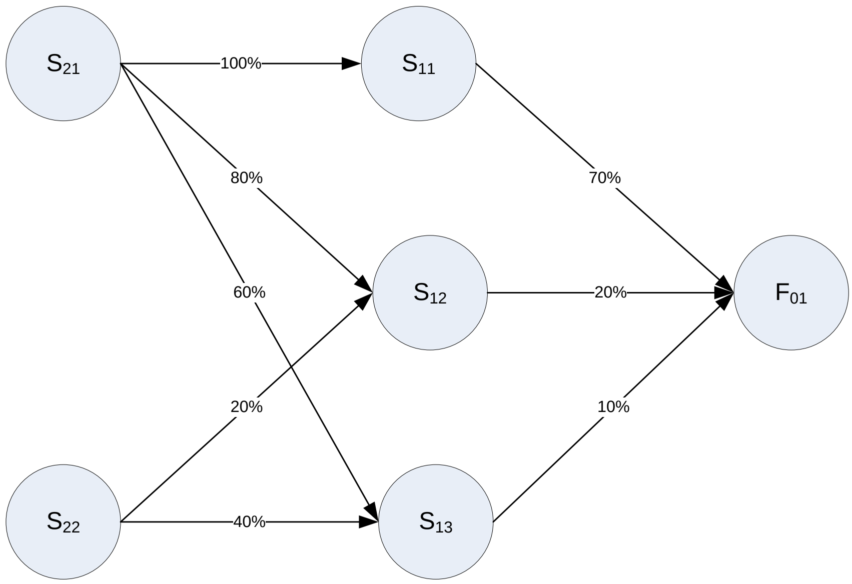

Figure 2: A sample supply chain network with with two stages of suppliers.

First, in the last row of $\boldsymbol{\Xi}$ we see that the focal firm F_{01} does not sell any products to agents within the network. For our purpose to study the downstream risk for this focal firm all connections to possible clients to F_{01} are naturally not considered. F_{01} herself receives all products or necessary components from all three direct suppliers, where for instance $\xi_{S_{11}F_{01}} = 0.7$ or $\xi_{S_{13}F_{01}} = 0.1$ (fifth row). A disruption in the production process of firm S_{11} (S_{13}) can induce a 70% (10%) reduction of delivery volume of F_{01}. On the other hand, for S_{11} all necessary components are sourced from *supplier S_{21}, for S_{12} components are sourced* 80%, 20% *from supplier* S_{21}, S_{22} *respectively.*

3.2 Disruption risk: frequency and severity

The hazard model characterizes the timing and severity of disruptive events on operations on the firm level (independent of the network). In the first part we introduce the necessary and allowedly complicated notation. We describe the timing of these events in each node under certain assumptions, then the severity or impact. We use the terms hazard event and disruption risk interchangeably. The realization of a hazard event is then called the supply chain disruption. The finite set $\mathcal{E} = \{e_1, \ldots, e_E\}$ collects all possible events of all suppliers in the network; $\mathcal{E}_j$ denotes the set of hazard events for node $j \in \mathcal{S}$. By definition $\mathcal{E} = \bigcup_{j \in \mathcal{S}} \mathcal{E}_j$. As in Wagner and Bode (2006) we distinguish two types of disruptions: events that impact a specific firm (idiosyncratic), and those with impacts across multiple firms (systematic). In formulae, the intersection of firm hazard event sets across firms is not necessarily empty, i.e., $\mathcal{E}_j \cap \mathcal{E}_i \neq \{\}$. For instance, two firms located at the south coast of the US identify 'hurricane' and 'machine malfunction' as hazard events. The latter hazard event is idiosyncratic whereas a hurricane has an impact on the production of both firms and is called systematic. The term systematic is only used for the simultaneous dependence of different firms in the network on the same hazard event and not the simultaneous impact because of interfirm links (contagion). A production disruption in node $j \in \mathcal{S}$ triggered by an event $e_i \in \mathcal{E}_j$ is described by the following properties[2]:

- *disruption times*, the points in time when a supply chain disruption occurs,
- *recovery times*, the time required to resolve the disruption,
- *interarrival times*, the time between successive malfunctions of the supply chain,
- *direct costs* at the node of the disruption, e.g., repair or property damage, and *indirect costs*, losses of production (in percentage terms) for connected nodes.[3]

Hazard events $e_i \in \mathcal{E}_j$ are assumed to take place according to a Poisson process $(N^{e_i}_{j,t})_{t>0}$ with intensity $\lambda^{e_i}_j$ and state space $\mathbb{N}_0$. After a disruption occurs the firm needs a random amount of time to resume the production process. Recovery times $(R^{e_i}_{j,n})_{n \in \mathbb{N}}$ are described by a sequence of independent and identically distributed (iid.) and positive random variables, where we set $r^{e_i}_j = \mathbf{E}[R^{e_i}_j]$. As soon as production starts, this process is again exposed to new disruptions. According to the assumption about Poisson distributed disruptions, active times are exponentially distributed, i.e., $A^{e_i}_{j,n} \sim \exp(\lambda^{e_i}_j)$, for all $n \in \mathbb{N}$. As illustrated above, hazard events can be both firm-specific and systematic, influencing the production processes of more than one firm

[2]In reduced form credit risk modeling it is usual to assume exponentially distributed waiting times for the next default (see for instance Lando (2009)), where at that time the creditor realizes directly a loss (credit amount minus recovery). For our setting this would imply that at one point in time production is interrupted, costs occur and already in the next time step the problem is solved and production can continue, which is of course unrealistic. Therefore we think that the interruption time structure of a certain event can be better modeled by a renewal-reward process

[3]Note, the terms direct and indirect costs are also used in the accounting literature, but with a different meaning.

simultaneously. The sum of the recovery and active times between two disruptions is termed the interarrival time. The whole time structure for a hazard event $e_i \in \mathcal{E}_j$ is given by (see Figure 3):

$$0 < T^{e_i}_{j,1} < T^{e_i}_{j,2} = T^{e_i}_{j,1} + R^{e_i}_{j,1} + A^{e_i}_{j,2} < T^{e_i}_{j,3} < \ldots < T^{i}_{j,m} < T. \tag{2}$$

The random sequence $T^{e_i}_{j,m} = X^{e_i}_{j,1} + \ldots + X^{e_i}_{j,m}$ with $X^{e_i}_{j,m} = T^{e_i}_{j,m} - T^{e_i}_{j,m-1}$ is termed a renewal process, where the random variable $T^{e_i}_{j,m}$ is the m^{th} disruption time for event e_i and firm j. Costs for a specific event are also represented by a sequence of positive iid. random variables, where the direct costs of event e_i for node j are denoted by $DC^{e_i}_j$ and are reported in absolute terms, while $(IC^{e_i}_{j,n})_{n\in\mathbb{N}}$ denotes the sequence of production reductions in percentage terms per unit time. The direct costs occur at node j, at which the process is disrupted. Indirect costs emerge for the direct neighboring firms of supplier j as a result of the purchasing volume relationships between the firms. Each random variable is associated with a respective density $f(x)$. We assume that the renewal-reward processes $((N^{e_i}_{j,t})_{t>0}, \lambda^{e_i}_j)$ are independent across all $e_i \in \mathcal{E}_j$ and cost processes $(R^{e_i}_j, DC^{e_i}_j, IC^{e_i}_j)$ are independent across all $j \in \mathcal{S}$ in addition. Note that the tuple $(R^{e_i}_j, DC^{e_i}_j, IC^{e_i}_j)_{e_i\in\mathcal{E}_j, j\in\mathcal{S}}$ describes only the firm-specific impact of a hazard event, because, in general, the impact of disruptions differs across firms due to differences in organization, financial structure, business continuity management etc.

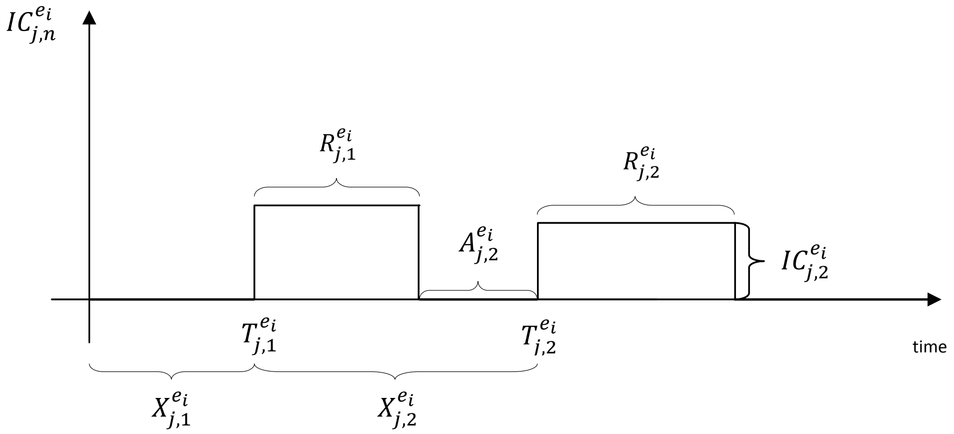

Figure 3: Basic disruption time structure of event e_i with costs $IC^{e_i}_{j,n}$, recovery times $R^{e_i}_{j,n}$, interruption times $T^{e_i}_{j,n}$, active times $A^{e_i}_{j,n}$ and interarrival times $X^{e_i}_{j,n}$.

3.2.1 Hazard events with no impact on recovery times

For the special case in which recovery times are non-stochastic and identical across hazard events, i.e., $R^{e_i}_{j,n} = r$ for all $e_i \in \mathcal{E}_j$ and $n \in \mathbb{N}$, the disruption process can be described as a superposition of Poisson processes. Let $(X_{j,n})_{n\in\mathbb{N}}$ be an independent family of interarrival times with parameter $\lambda_j = \sum_{e_i\in\mathcal{E}_j} \lambda^{e_i}_j$ and $F(X_{j,m} \leq b) = 1 - e^{-\lambda_j(b+r)}$, $b \in \mathbb{R}$. $T_{j,n}$ is the time of the n-th disruption of firm j. We set

$$T_{j,n} := \sum_{m=1}^{n} X_{j,m} \quad \text{and} \quad N^j_t := \#\{n \in \mathbb{N}_0 : T_{j,n} \leq t\} \tag{3}$$

as the counting process for firm j, independent of the specific hazard event. Under normal circumstances, we must rely on MC simulation for the analysis since recovery times are random and vary across hazard events. Here we impose this strong assumption to obtain a compact expression.

3.2.2 Hazard events with an impact on recovery times

One can argue that disruptions during the recovery time do not influence the interruption status of the firm (as seen in Subsection 3.2.1) or that the occurrence of a hazard event during the recovery time just destroys the recovery progress and therefore the repair process starts again with the fixed time. Therefore the recovery time will be prolonged randomly (see Figure 4). The production process of firm j is disrupted by hazard event e_2 following a fixed recovery time of $r_j^{e_2}$. During this time a second event e_1 occurs and the recovery process start again with $r_j^{e_1}$. Also the third event e_3 interrupts the build up period. Not till then the production process can continue. The random recovery time starting at disruption time $\tau_1^{e_1} = T_{j,1}$ is then given by

$$\begin{aligned} R_1^{e_i} &= r^{e_2} + \Delta\tau_2^{e_1} + \Delta\tau_3^{e_3} \\ &= r^{e_2} + Z_1, \end{aligned}$$

where the *prolonged recovery time* $(Z_n)_{n\in\mathbb{N}}$ is a r.v. dependent on the number of diruptions during the recovery periods, which is random.

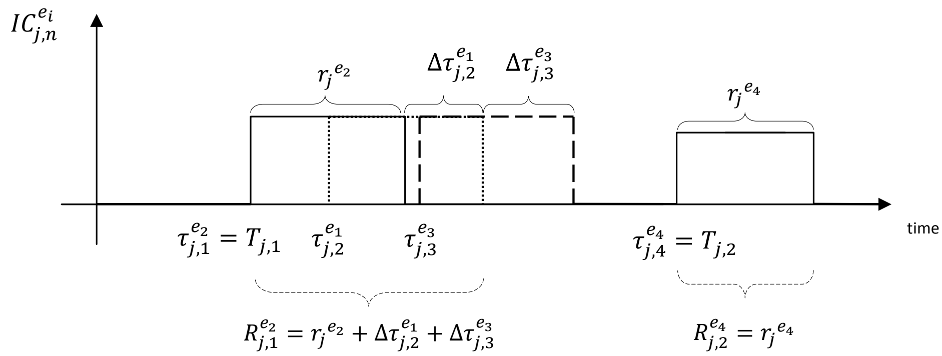

Figure 4: Firm specific disruption time structure when disruptions of hazard events e_1 and e_3 during the recovery time are anticipated. The total recovery time is prolonged randomly.

3.3 Loss dispersion

Besides concentrating on the event frequency we have to incorporate the impact of these disruptions (severity). How disruptions propagate through the network will be the topic of this subsection. Correlations across nodes in the network are established due to two factors: systematic risk, in which the intersection of firm specific hazard event sets is not necessarily empty, and contagion, in which the network naturally produces interfirm dependency, allowing idiosyncratic disruptions to disperse through the network and affect other firms.

Indirect costs - one stage

The impact of systematic hazard events can be partially described by (4). The total indirect costs in relative terms of hazard event e_i with respect to direct neighboring firms (not only the focal firm) in the deterministic network up to time t are given by:

$$TIC^{e_i}(t) := \sum_{\{j \in \mathcal{S} | e_i \in \mathcal{E}_j\}} \left(\sum_{k=1}^{N^{e_i}_{j,t}} IC^{e_i}_{j,k} \, R^{e_i}_{j,k} \Big(\sum_{l>j} \xi_{jl} \Big) \right). \tag{4}$$

In equation (4) all firms with an exposure regarding hazard event e_i are collected. The result is given in relative terms, i.e., the entries of $\mathbf{\Xi}$ are given in percentage terms of delivery volume. To obtain the absolute loss of one hazard event one has to add the absolute values of volume for any firm which is influenced by a disruption of node j.

Example 3.2. *Coming back to our SCN of Example 3.1. We introduce additionally a subset of hazard events $\mathcal{E}_{S_{11}} \cap \mathcal{E}_{S_{21}} \subseteq \mathcal{E}$ with $\mathcal{E}_{S_{11}} = \{e^h, e^d_{S_{11}}\}$ and $\mathcal{E}_{S_{21}} = \{e^h, e^d_{S_{21}}\}$. Firms S_{11} and S_{21} have exposure to a firm specific hazard event and one common event (hurricane). We are interested in the indirect costs of these hazard events. We assume for a horizon of 180 days the following realizations in Table 1. During the period under consideration only one hurricane*

	$e^d_{S_{21}}$	e^h	$e^d_{S_{11}}$
	$N^{e^d_{S_{21}}}_{S_{21},t} = 0$	$N^{e^h}_t = 1$	$N^{e^d_{S_{11}}}_{S_{11},t} = 2$
$k = 1$		$IC^{e^h}_{S_{11},1} = 0.3$	$IC^{e^d_{S_{11}}}_{S_{11}} = 0.5$
		$IC^{e^h}_{S_{21},1} = 0.5$	
		$R^{e^h}_{S_{11},1} = 12$	$R^{e^d_{S_{11}}}_{S_{11},1} = 3$
		$R^{e^h}_{S_{21},1} = 40$	
$k = 2$			$IC^{e^d_{S_{11}}}_{S_{11},2} = 0.6$
			$R^{e^d_{S_{11}}}_{S_{11},2} = 4$

Table 1: Realizations for indirect costs in relative terms, recovery times and hazard frequency for firms S_{11} and S_{21}. The considered hazard events are $\mathcal{E} = \{e^d_{S_{11}}, e^d_{S_{21}}, e^h\}$. The first two events are firm specific, the last affects both firms with different magnitude.

occurs. However, the impact on node S_{21} is quite dramatic. Only 50% of the operations can be continued for the next 40 days. The indirect downstream costs of the hazard event hurricane e^h can be calculated in line with equation (4):

$$\begin{aligned} TIC^{e^h}(t) :&= \sum_{j \in \{S_{11}, S_{21}\}} IC^{e^h}_{j,1} \, R^{e^h}_{j,1} \Big(\sum_{l>j} \xi_{jl} \Big) \\ &= 0.3 \times 12 \times 0.7 + 0.5 \times 40 \times (1 + 0.8 + 0.6). \end{aligned}$$

To sum up, the hazard event e^h affects nodes S_{11} and S_{21} in the SCN. During 180 days a hurricane occurs once and induces a business reduction in node S_{11} of 30% for 12 days. S_{11} is *one of the suppliers of F_{01} ($\xi_{S_{11}F_{01}} = 0.7$) which results in losses for F_{01} of $0.3 \cdot 12 \cdot 0.7$, analog for node S_{21}.*

Propagation mechanism

For the second aspect of correlated losses, we must define a mechanism that allows disruptions that occur on farther stages to affect other firms in the network including the focal firm. The $n-$th power of the matrix $\boldsymbol{\Xi}$ power of the matrix describes the impact on firms from respective suppliers on the n-th stage exclusively (without disruptions on intermediate stages). We assume that there is no inventory to absorb parts of potential supplier disruptions; this implies that losses are transferred without friction. In practice, disruptions occur simultaneously across nodes in the SCN. We incorporate the effects of each disruption event and associated losses separately but impose the constraint that aggregated losses do not exceed the indirect losses of direct neighbors; i.e., for each disruption, we follow the complete path in the network. Hence, the propagation of losses from one stage to the next is restricted to the maximum loss of the nearer (or next) stage.

Example 3.3. *We illustrate the propagation of losses (see Figure 2) with*

$$\boldsymbol{\Xi}^1 = \begin{pmatrix} 0 & 0 & 1 & 0.8 & 0.6 & 0 \\ 0 & 0 & 0 & 0.2 & 0.4 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.7 \\ 0 & 0 & 0 & 0 & 0 & 0.2 \\ 0 & 0 & 0 & 0 & 0 & 0.1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \quad \textit{and} \quad \boldsymbol{\Xi}^2 = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0.92 \\ 0 & 0 & 0 & 0 & 0 & 0.08 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix},$$

where $\boldsymbol{\Xi}^2$ is just $\boldsymbol{\Xi}^1$ squared. If we consider $\boldsymbol{\Xi}^2$ we see that node S_{21} is indirectly linked to the focal firm F_{01}. If a disruption in S_{21} occurs the neighbors S_{11}, S_{12} and S_{13} are directly affected (first row of $\boldsymbol{\Xi}^1$) and therefore through the direct links from the first stage also the focal firm. The entry $\xi^2_{S_{21}F_{01}} = 0.92$ characterizes this propagation of losses through the network. Let us assume that S_{21} as well as S_{12} are dependent on e^h. So, the occurrence of this event induces disruptions in both nodes, where we assume that the recovery time is set to one for both firms but $IC^{e^h}_{S_{21}} = 0.5$ and $IC^{e^h}_{S_{12}} = 0.1$. Then the costs for F_{01} induced by e^h can be calculated by

$$\begin{aligned} V^{e^h}_{F_{01}} &= IC^{e^h}_{S_{21}} R^{e^h}_{S_{21}} \xi_{S_{21}S_{11}} \xi_{S_{11}F_{01}} \\ &\quad + \min\{IC^{e^h}_{S_{21}} R^{e^h}_{S_{21}} \xi_{S_{21}S_{12}} + IC^{e^h}_{S_{12}} R^{e^h}_{S_{12}} \xi_{S_{12}F_{01}}, R^{e^h}_{S_{12}} \xi_{S_{12}F_{01}}\} \\ &\quad + IC^{e^h}_{S_{21}} R^{e^h}_{S_{21}} \xi_{S_{21}S_{13}} \xi_{S_{13}F_{01}} \\ &= 0.5 \times 0.7 + \min\{0.5 \times 0.8 \times 0.2 + 0.1 \times 0.2, 0.2\} + 0.5 \times 0.6 \times 0.1 \\ &= 0.35 + \min\{0.1, 0.2\} + 0.06 \\ &= 0.51. \end{aligned}$$

The correlation structure of disruptions in the network is very important for the shape of the loss distribution. Below, we discuss the impact of two basic diversification strategies that aim to decouple existing linkages and therefore to mitigate exposure due to high correlation. We distinguish the dependency reduction on one stage (vertical) and across two stages (horizontal). Our interest is whether, and under which conditions, management may choose a network structure that can improve the risk exposure of the focal firm.

Vertical diversification

Example 3.4. *We illustrate the aspect of common hazard events on aggregated losses for the focal firm in a simple setting. We compare two cases: first, we calculate the total loss of focal firm* F_{01} *assuming that there exist only two suppliers with* $\mathcal{E}_{S_{11}} \cap \mathcal{E}_{S_{12}} = \{e^h\}$*; one corresponding disruption process, which is identical for both firms,* $N_t^{e^h}$ *with* λ^{e^h}*; no recovery time, purchasing volumes of* $\xi_{S_{11}F_{01}} = \xi_{S_{12}F_{01}} = 50\%$ *each and* $IC^{e^h_{S_{11}}}(t) = IC^{e^h_{S_{12}}}(t) = 1$ *for all* t*– i.e., if a disruption occurs, losses of 100% occur for the focal firm. Then, we investigate the case, in which one of the firms is relocated and both firms are exposed to different (independent) hazard events that occur with the same probability. All other assumptions are still in place. Formally,* $\mathcal{E}_{S_{11}} = \{e^{h_1}\}$*,* $\mathcal{E}_{S_{12}} = \{e^{h_2}\}$ *and* $N^{e^{h_1}}_{S_{11},t}$*,* $N^{e^{h_2}}_{S_{12},t}$ *independent and* $\lambda^{e^h} = \lambda^{e^{h_1}}_{S_{11}} = \lambda^{e^{h_2}}_{S_{12}}$*. In the first case, the expected total loss*[4] *up to time* t *is given using Wald's equation,*

$$\mathbf{E}[V_t] = \mathbf{E}[\sum_{k=1}^{N_t^{e^h}} (\xi_{S_{11}F_{01}} + \xi_{S_{12}F_{01}})] = \mathbf{E}[N_t^{e^h}] = \lambda^{e^h} t$$

and the variance is given, using the law of total variance

$$\begin{aligned}\mathbf{Var}[V_t] &= \mathbf{E}[\mathbf{Var}[V_t|N_t^{e^h}]] + \mathbf{Var}[\mathbf{E}[V_t|N_t^{e^h}]]\\ &= \mathbf{E}[N_t^{e^h}\mathbf{Var}[IC^{e^h}_{S_{11}}]] + \mathbf{Var}[N_t^{e^h}\mathbf{E}[IC^{e^h}_{S_{11}}]]\\ &= \mathbf{Var}[1]\mathbf{E}[N_t^{e^h}] + \mathbf{E}[1]^2\mathbf{Var}[N_t^{e^h}]\\ &= \lambda^{e^h} t.\end{aligned}$$

Analogously, we easily obtain the expected loss for the second case:

$$\mathbf{E}[V_t] = \mathbf{E}[\frac{1}{2}\sum_{k=1}^{N^{e^{h_1}}_{S_{11},t}} IC^{e^{h_1}}_{S_{11},k} + \frac{1}{2}\sum_{k=1}^{N^{e^{h_2}}_{S_{12},t}} IC^{e^{h_2}}_{S_{12},k}] = \frac{1}{2}(\lambda^{e^{h_1}}_{S_{11}} + \lambda^{e^{h_2}}_{S_{12}})t = \lambda^{e^h} t.$$

Using the independence of both processes the variance is given by

$$\mathbf{Var}[V_t] = \frac{1}{4}t(\lambda^{e^{h_1}}_{S_{11}} + \lambda^{e^{h_2}}_{S_{12}}) = \frac{1}{2}t\lambda^{e^h}.$$

The relocation of one firm to an area in which the firm is exposed to the same risk in terms of expected losses and variance induces the same expected total loss V_t *but a 50% reduced variance for the focal firm. Therefore, the loss distribution in a framework with less correlation exhibits a lower dispersion. We thus expect fatter tails for highly correlated networks.*[5]

[4] V_t is of course well known under the term compound Poisson process.

[5] Due to the independence of the processes the calculations can be easily extended to N firms where the variance is reduced to zero in the limit (diversification effect).

Horizontal diversification

In Example 3.4, we have seen that diversification on one stage can be very successful in reducing uncertainty. If we also anticipate the effects of other stages, the situation is different: if the production of a firm in the SCN totally breaks down, in Example 3.3 firm S_{12}, all simultaneous disruptions one stage before, so losses from the suppliers S_{21} and S_{22} are totally irrelevant for the focal firm because there is no propagation. This is an extreme case because the loss potential is directly wiped out. However, clear statements in favor of diversification are more difficult, as shown in the simulation results below.

Example 3.5. *We consider one path in a two-stage supplier network, comprising supplier S_{11} on tier one, S_{21} on tier two and the focal firm F_{01}. We conduct an analysis similar to that in Example 3.4, but investigate the effects of diversification across stages. In the first case, all firms are dependent on the same hazard event e^h with corresponding disruption process $(N_t^{e^h}, \lambda^{e^h})$. In case of a disruption, the recovery time is one day for all times and events. The expected loss is given by*

$$\begin{aligned}
\mathbf{E}[V_t] &= \mathbf{E}[\sum_{k=1}^{N_t^{e^h}} \min\{IC_{S_{21},k}^{e^h}\,\xi_{S_{21}S_{11}}\xi_{S_{11}F_{01}} + IC_{S_{11},k}^{e^h}\,\xi_{S_{11}F_{01}}, \xi_{S_{11}F_{01}}\}] \\
&= \mathbf{E}[\sum_{k=1}^{N_t^{e^h}} \xi_{S_{11}F_{01}} \min\{IC_{S_{21},k}^{e^h}\,\xi_{S_{21}S_{11}} + IC_{S_{11},k}^{e^h}, 1\}] \\
&= \lambda^{e^h} t\,\xi_{S_{11}F_{01}}\mathbf{E}[\min\{IC_{S_{21}}^{e^h}\xi_{S_{21}S_{11}} + IC_{S_{11}}^{e^h}, 1\}] \\
&= \lambda^{e^h} t\,\xi_{S_{11}F_{01}}\big(\int_0^1 x\, f_C(x)\, dx + \int_1^\infty f_C(x)\, dx\big) \qquad (5)
\end{aligned}$$

where $f_C(x)$ denotes the density of the r.v. $C = IC_{S_{21}}^{e^h}\xi_{S_{21}S_{11}} + IC_{S_{11}}^{e^h}$. By writing the sum as the product of expected values, we implicitly assumed that the Poisson and indirect cost process are independent. Moreover, we omit the index k indicating that the r.v.s are identically distributed. Losses are bounded above by $\lambda^{e^h} t\,\xi_{S_{11}F_{01}}$, the maximum loss of the nearest connection to the focal firm weighted by the expected number of disruptions.
In the second case, we assume that both suppliers are dependent on two different hazard events e^{h_1} in S_{21} and e^{h_2} in S_{11}. We obtain

$$\begin{aligned}
\mathbf{E}[V_t] &= \mathbf{E}[\sum_{k=1}^{N_{S_{21},t}^{e^{h_1}}} IC_{S_{21},k}^{e^{h_1}}\,\xi_{S_{21}S_{11}}\xi_{S_{11}F_{01}} + \sum_{k=1}^{N_{S_{11},t}^{e^{h_2}}} IC_{S_{11},k}^{e^{h_2}}\,\xi_{S_{11}F_{01}}] \\
&= \xi_{S_{11}F_{01}}\big(\lambda_{S_{21}}^{e^{h_1}} t\xi_{S_{21}S_{11}}\mathbf{E}[IC_{S_{21}}^{e^{h_1}}] + \lambda_{S_{11}}^{e^{h_2}} t\mathbf{E}[IC_{S_{11}}^{e^{h_2}}]\big) \qquad (6)
\end{aligned}$$

In the special case, in which all intensities are equal, equation (6) can be rewritten as

$$\mathbf{E}[V_t] = \lambda^{e^h} t\xi_{S_{11}F_{01}}\big(\mathbf{E}[IC_{S_{21}}^{e^{h_1}}]\xi_{S_{21}S_{11}} + \mathbf{E}[IC_{S_{11}}^{e^{h_2}}]\big). \qquad (7)$$

Relocation of a supplier (on a different stage) in order to decouple the stochastic dependence is *obviously reasonable considering the expected losses in equations* (5) *and* (7) *if the term within the brackets of the latter formula is smaller than it was in equation* (6)*. For this we have to consider the size of indirect costs of both firms but also changing intensities. The interesting result is that a relocation of a supplier should not be considered if the expression within the brackets is greater than one, while if the expected loss of S_{11} is relatively small, the potential of losses above the threshold is small and therefore reducing the correlation structure may be an option. For the variance we refer to the calculations in Appendix B.*

4 Implementation

4.1 Simulation setting

Up to this point, we have calculated single loss realizations in idealized examples with the aim of illustrating particular aspects and mechanics of our modeling approach, but have not employed the aspects of randomness and the interaction of the model input parameters. In this section, we implement a sufficiently simple example of SCN configuration and generate a loss distribution for the focal firm via Monte Carlo simulation. This allows the study and comparison of the impacts of different network topologies and modeling approaches on the loss distribution. Our results are presented in terms of expected losses and established tail risk measures such as Value at Risk or Expected Shortfall.

We always consider the same global network structure depicted in Figure 2 and described by the adjacency matrix (1) (for reference of a similar network design, see Cossin and Schellhorn (2007)). At the beginning of each simulation run, we incorporate only the first stage of suppliers. In the next step we also account for the second stage. After assuming total disruptions (indirect costs of 100%) we run simulations with and without varying indirect costs as described in Subsection 3.2. We will see that the model specification is of utmost importance for determining the loss distribution. Note that we do not work with a calibrated model where we can make conclusions about absolute losses. We instead conduct a comparative statics analysis in which we describe consequences for the focal firm in relative terms (i.e., relative to other models or network presettings). With the results of this analysis, we infer managerial implications in the next section.

The time horizon is set to 180 days and we perform 1000 MC iterations. We investigate different specifications for the time structure of events which were described in Subsection 3.2.1 and following. First, we assume that there exist two idiosyncratic hazard events for each firm. Therefore, we simulate two independent Poisson processes with corresponding intensities on each node; the intensities are shown in the first columns of Table 2. The intensities refer to days as time units. A value of 0.01 corresponds to a mean arrival rate during 180 days of 1.8 malfunctions. Later we also incorporate a third hazard event e^h, which can have an impact on more than one firm in the network. This hazard event e^h has an impact on all suppliers; we simulate one Poisson process with intensity 0.001 so that the time structure $(T^{e^h}_{j,m})_m$ of this event is the same for all firms. In our analysis we distinguish between events which have no impact during the recovery time and those where there is the possibility of randomly prolonged recovery times (PRT), as described in Subsection 3.2.2. We set the average recovery time $r_j^{e_i}$ of 3 days for hazard events e^1 and e^2, and 14 days for hazard events e^h for all firms. We report mean and tail risk measures Value at Risk (VaR) and Expected Shortfall (ES) for a confidence level of 95%.

Hazard Event 1	**Hazard Event 2**	**Hazard Event 3**
$\lambda^{e^1_{S_{11}}} = 0.01$	$\lambda^{e^2_{S_{21}}} = 0.01$	$\lambda^{e^h_{S_{21}}} = 0.001$
$\lambda^{e^1_{S_{12}}} = 0.015$	$\lambda^{e^2_{S_{22}}} = 0.005$	$\lambda^{e^h_{S_{22}}} = 0.001$
$\lambda^{e^1_{S_{13}}} = 0.01$	$\lambda^{e^2_{S_{11}}} = 0.01$	$\lambda^{e^h_{S_{11}}} = 0.001$
$\lambda^{e^1_{S_{21}}} = 0.02$	$\lambda^{e^2_{S_{12}}} = 0.05$	$\lambda^{e^h_{S_{12}}} = 0.001$
$\lambda^{e^1_{S_{22}}} = 0.01$	$\lambda^{e^2_{S_{13}}} = 0.01$	$\lambda^{e^h_{S_{13}}} = 0.001$

Table 2: Intensities of hazard events.

4.2 Results

4.2.1 Loss dispersion across stages

In the first step, we calculate the losses for focal firm F_{01} induced by disruptions from the three direct suppliers S_{11}, S_{12}, S_{13} and ignore the second stage. The SCN is described by the following weighting matrix:

$$\boldsymbol{\Xi} = \begin{pmatrix} 0 & 0 & 0 & 0.7 \\ 0 & 0 & 0 & 0.2 \\ 0 & 0 & 0 & 0.1 \\ 0 & 0 & 0 & 0 \end{pmatrix} . \tag{8}$$

When we run simulations with the standard values of intensities reported in Table 2, we do not observe significant differences in reported risk measures with and without prolonged recovery times (PRT). The average difference in all risk measures between the two categories is around 1.3%. The results are summarized in Table 3. For the PRT case there is a probability of 5% that losses (days of production stoppage) for the focal firm during 180 days exceed the VaR of 22.2. Therefore, we conduct simulations with intensities five times higher (see Table 4). With

Type	**Mean**	**VaR**	**ES**
One-stage without PRT	14.64	21.6	24.16
One-stage with PRT	14.88	22.2	24

Table 3: Loss distribution characteristics: one stage.

these new intensities, we observe naturally an absolute increase in all risk measures. Now, the average increase in the respective risk measures is with 3.2% more pronounced when we allow

PRT. For making reasonable statements about the risk status of a given supply chain network the classification of hazard events and their interaction is fundamental.

Type	Mean	VaR	ES
One-stage without PRT	56.26	67.7	70.68
One-stage with PRT	57.9	70.3	72.88

Table 4: Loss distribution characteristics: one stage (increased intensities).

Disruptions can now take place in the first stage and in the nodes S_{21}, S_{22}. Here, we follow Subsection 3.3 where we described the dispersion of losses emerging on stages of higher order than the first. As an analogue to the first step, we also incorporate the possibility of prolonged recovery times. The results are reported in Table 5. The fact that we include more than one risk factor (as compared to the model proposed by Deleris, Elkins, and Paté-Cornell (2004)) offers the possibility of investigating the effects of interacting hazard events. The introduction of the second stage induces a higher and a broader spectrum of losses. All values increase up to 2.5% on average when PRT is allowed.

Type	Mean	VaR	ES
Two-stage without PRT	24.2	34.32	36.9
Two-stage with PRT	24.8	35.32	37.7

Table 5: Loss distribution characteristics: two stages.

4.2.2 Correlation effects

In this subsection, we investigate more closely the interaction of the two correlation effects between nodes in the network, namely the dependency created by hazard events across firms (nonempty intersection between the event sets) and by the network topology. The question at hand is whether a diversification strategy is always the dominant decision rule for managing the SCN. We show that this is not necessarily the case. In Example 3.4, we show analytically that the dependence reduction between two firms on the same stage (vertical diversification) induces a more centered (measured in variance terms) loss distribution for the focal firm. In Example 3.5, we calculate expressions for expected value and variance of losses if the focal firm has one supplier on the first stage and that supplier has itself one supplier on the second stage. These two horizontally aligned firms are either both dependent on the same hazard event or on different hazard events (horizontal diversification). We see that clear implications in this general setting are not possible since many parameters influence the results. In particular, the transmission mechanism from one stage to the other stage is pivotal for this analysis.

We simulate Example 3.4, i.e., in the first case we have two independent Poisson processes with the same intensity equal to 0.2. In the second case we have one process with intensity

0.2 but affecting both suppliers. Purchasing volumes are uniform and equal to 50% for each supplier. The results are presented in Table 6.[6] The variance resulting from simulations is equal to 16.56 in the former case and 29.53 in the latter. From that result we would infer that risk can be reduced by making suppliers independent of the same hazard event (vertical diversification). Next, we investigate the correlation effects embedded in the complete network structure. We assume that all suppliers (first and second stage) are located in the same geographical region and therefore exposed to the same type of hazard event. If the event strikes, all facilities are damaged and suffer from production delays of 14 days. We compare the loss distributions of the same system, where the disruption processes are either independent or replaced by one hazard event. The results are reported in Table 7. All risk measures are slightly higher in the case where disruptions are independent. On the one hand, we can attribute this observation to the fact, that the sum of intensities of the independent Poisson processes is higher than the intensity of a single Poisson process; thus, it leads to a relatively higher number of disruptions. On the other hand, in a situtation where disruptions are perfectly correlated, the propagation mechanism prevents the complete contagion of losses through the network.

Type	**Mean**	**VaR**	**ES**	**Variance**
Independent processes	32.6	39.5	40.75	16.56
One process	33	42	44.26	29.23

Table 6: Loss distribution characteristics: two suppliers one stage.

Type	**Mean**	**VaR**	**ES**	**Variance**
Independent processes	28	41.6	47.47	63.3
One process	26.3	40.4	46.2	61.2

Table 7: Loss distribution characteristics: two stages.

Next, we study how the uncertainty of production reductions affects the loss distribution. For that purpose we compare the disruptions occurring across both stages, where expected production reductions on the first stage is lower than the production reductions on the second stage. Correspondingly, we generate random numbers from a Gaussian distribution with a mean of 0.2 and standard deviation of 0.1 on the first stage, and Gaussian with a mean of 0.8 and standard deviation of 0.1 on the second stage.

Table 8 illustrates how misleading it can be when managers make their decision based only on the mean value of losses. The correlation effects are first visible, when we compare the tails of the distribution. In contrast to the case before, where we assumed that production

[6]The small deviations from the analytical results can be justified by the number of simulations and the implemented random number generator, where we have to discretize the numbers to obtain disruption 'days' for a reasonable interpretation.

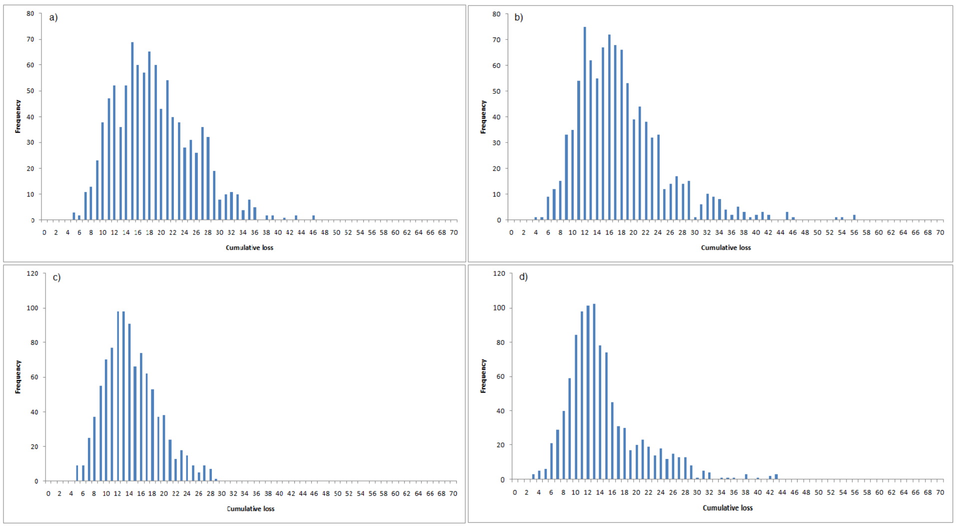

Figure 5: Loss distributions for a sample 2-stage supply chain network. The original structure: independent processes (a) and one process (b). The reconfigured structure: independent processes (c) and one process (d).

Type	**Mean**	**VaR**	**ES**
Independent processes	18.4	30.48	34.37
One process	17.34	31.64	37.38
Independent processes reconfigured	13.87	22.84	25.05
One process reconfigured	14	26.75	31

Table 8: Loss distribution characteristics: sample network with 2 stages. Indirect costs varying between stages.

breaks down completely, the relative difference in VaR and ES is significantly higher here, when disruptions occur simultaneously. The reason is again the propagation mechanism, because now the cost potential of disruptions on neighboring stages is not wiped out directly. Based on the observed results, we then make a hypothetical decision about the reconfiguration of the purchasing volumes in the network. We decide to switch the business volumes between supplier S_{11}, S_{12} and S_{13}. The new business volumes are: $\xi_{11} = 0.1$, $\xi_{12} = 0.2$ and $\xi_{13} = 0.7$. The effects of this decision can be seen in the decrease of all risk measures. The decision to reconfigure the network was correct, as it lowered the company's overall risk exposure.

5 Implications and conclusions

5.1 Managerial implications

In this section, we draw some important conclusions for SCN design in general and for the managerial decision process in particular. First, we notice that the classification and estimation of the frequency and severity of hazard events is important for an accurate loss distribution calculation. In the case of high frequency events, the random prolongation of recovery times contributes to the tails of the loss distribution. Firms should establish an internal database for losses due to disruptions in its SCN. All entities in the SCN including the focal firm can be characterized by the set of geographic, operational and financial metrics that should be gathered and evaluated prior to the risk management process. In collaboration with a large insurance company, we specify the data requirements necessary to calculate the losses with the proposed model (see Table 6). Moreover, to obtain full information about risk, one also needs the corresponding likelihood of occurrence and the impact of all possible hazard events. The probability and recovery time for each event have to be estimated by expert knowledge and time series analysis (see for instance the International Disaster Database of the Centre for Research on the Epidemiology of Disasters (CRED), or loss data providers like Algorithmics, Inc.). Another lesson we can learn from our theoretical and numerical results concerns the diversification of supplier portfolios and networks. The chief contribution of our method is the bottom-up reconstruction of the correlations caused by the dependencies among suppliers. The reconfiguration of the supplier base in the first stage can lead to substantial improvement of the focal firm's risk profile. In some simple cases it is very clear that the more suppliers we have in our portfolio the lower the variance induced by disruptions. In cases where we add more stages to the existing SCN, however, conclusive statements are not straightforward. In these simulations, we observed situations where the accumulation of negative network effects exceeds the benefits of diversification on the first stage of suppliers. This approach helps us to quantify the impact of a reconfigured SCN on the company's risk exposure. This observation contributes to the understanding of diversification effects, studied by Babich, Burnetas, and Ritchken (2007) and Wagner, Bode, and Koziol (2009).

5.2 Conclusions

The goal of this paper is to propose a model for the calculation of the loss distribution from disruptions in a SCN. This gives supply chain risk managers an efficient tool for the quantification of supply chain risks, intrinsically embedded in the existing network design. We employed generalized semi-Markov processes for simulating disruptions in each node and these disruptions' interaction across the network, where we allowed a broad set of hazard events. For the modeling of disruptions from single hazard events, we used renewal-reward processes. Their structure corresponds to the typical production disruption we have in mind. Moreover, we described and categorized different classes of hazard events with respect to interaction issues. This approach allowed us to incorporate the correlation effects among different groups of hazard events. Most of the modeling aspects were illustrated in simple examples where we also inferred some implications regarding expected losses or distributional properties in stylized situations. After implementing the model and simulating a hypothetical supply chain network with different specifications, we can infer some interesting and also counterintuitive results. With this framework, we hope to reproduce the mechanisms of disruption propagation across the network in a more sophisticated and transparent way than in conventional models. A better understanding of how supply chain design affects supply chain risk exposure enables operations managers to structure their supply chains in a way that is in line with the firms' willingness to take risks and thus facilitates better supply chain design decision making.

We are certainly aware of the limitations of our model. The simulations we carried out were based on idealized examples and have not been validated with real data. Nevertheless, the modeling environment and parameter values have been discussed in several meetings with insurance and manufacturing companies' representatives to assure the plausibility of our approach. Naturally, the next step would be to apply our model to a real-world case. The matrix notation of purchasing volumes allowed us to describe the topology of the supply chain network in a very efficient manner. Here, we concentrated only on the downstream risk arising from supplier disruptions. In general, however, firms are also exposed to upstream risks originating from customers (e.g., customer defaults or demand fluctuations). In our framework, we decided to keep the number of parameters to the minimum; therefore, we did not include inventories either, which may have had a moderating effect on the recovery times. As we mentioned in the introduction, the heterogeneity of disruptions is an important and difficult issue to tackle. Here, we assumed that the recovery times and intensities for the hazard process are deterministic. One of the possible extensions of our model is to introduce stochastic recovery times and time-varying intensities. The evolution of the supply chain network is another interesting aspect of SCNs observed in reality. Agent-based simulation techniques are an interesting research avenue, as well. In terms of risk-weighted network optimization, it would be desirable to automatize the reconfiguration algorithm, thus providing managers with an efficient software tool for supply chain network design, one which is not solely based on the reduction of production costs but takes into account the risk profile of the company.

Appendix A Data requirements

	Suppliers	Focal Firm	Customers
Geographical measures			
Variable • Plant location	**Description** •Geographical locations of suppliers' plants.	**Description** •Geographical locations of focal firm's plants.	**Description** •Geographical locations of customers' plants.
Operational measures			
Variable • Production volume • Capacity • Estimated downtime (optional)	**Description** • Total production's output measured as number of units produced. •Number of operating machines and their utilization for every plant location. •Average time required to recover from a specific disruption.	**Description** •Total production's output measured as number of units produced. •Number of operating machines and their utilization for every plant location. •Average time required to recover from a specific disruption.	**Description** •Total production's output measured as number of units produced. •Number of operating machines and their utilization for every plant location. •Average time required to recover from a specific disruption.
Financial measures			
Variable • Fixed capital • Working capital • Income	**Description** •Value of properties such as buildings, installations and machines. Calculated for every plant location. •Cash-flow calculated for the unit of time under consideration for every plant location. •Revenues generated by each production plant.	**Description** •Value of properties such as buildings, installations and machines. Calculated for every plant location. •Cash-flow calculated for the unit of time under consideration for every plant location. •Revenues generated by each production plant.	**Description** •Value of properties such as buildings, installations and machines. Calculated for every plant location. •Cash-flow calculated for the unit of time under consideration for every plant location. •Revenues generated by each production plant.

Figure 6: Data requirements.

Appendix B Calculations

To Example 3.5 – calculation of the variance: first, all firms are dependent on the same hazard event e^h with corresponding disruption process $(N_t^{e^h}, \lambda^{e^h})$. The following expression gives the total loss for the focal firm F_{01} up to time t:

$$V_t = \sum_{k=1}^{N_t^{e^h}} \min\{IC_{S_{21},k}^{e^h}\, \xi_{S_{21}S_{11}}\xi_{S_{11}F_{01}} + IC_{S_{11},k}^{e^h}\xi_{S_{11}F_{01}}, \xi_{S_{11}F_{01}}\} =: \sum_{k=1}^{N_t^{e^h}} M_k^{e^h}. \tag{9}$$

We set again $C = IC_{S_{21}}^{e^h}\, \xi_{S_{21}S_{11}} + IC_{S_{11}}^{e^h}$ and $f_C(x)$ denotes the corresponding density function. Then we obtain again with the law of total variance where we neglect the index k because the indirect costs are identically distributed:

$$\begin{aligned}
\mathbf{Var}[V_t] &= \mathbf{E}[\mathbf{Var}[V_t|N_t^{e^h}]] + \mathbf{Var}[\mathbf{E}[V_t|N_t^{e^h}]] \\
&= \mathbf{E}[N_t^{e^h}\mathbf{Var}[M^{e^h}]] + \mathbf{Var}[N_t^{e^h}\mathbf{E}[M^{e^h}]] \\
&= \mathbf{Var}[M^{e^h}]\,\mathbf{E}[N_t^{e^h}] + \mathbf{E}[M^{e^h}]^2\,\mathbf{Var}[N_t^{e^h}] \\
&= \lambda^{e^h} t\big(\mathbf{Var}[M^{e^h}] + \mathbf{E}[M^{e^h}]^2\big) \\
&= \lambda^{e^h} t\mathbf{E}[(M^{e^h})^2] \\
&= \lambda^{e^h} t\xi_{S_{11}F_{01}}^2\big(\big(\int_0^1 x^2\, f_C(x)\, dx + \int_1^\infty f_C(x)\, dx\big)\big)
\end{aligned} \tag{10}$$

In the second case, we assume that both suppliers are dependent on two different hazard events e^{h_1} in S_{21} and e^{h_2} in S_{11}. For the total loss we write

$$\begin{aligned}
V_t &= \sum_{k=1}^{N_{S_{21},t}^{e^{h_1}}} IC_{S_{21},k}^{e^{h_1}}\, \xi_{S_{21}S_{11}}\xi_{S_{11}F_{01}} + \sum_{k=1}^{N_{S_{11},t}^{e^{h_2}}} IC_{S_{11},k}^{e^{h_2}}\, \xi_{S_{11}F_{01}} \\
&=: \sum_{k=1}^{N_{S_{21},t}^{e^{h_1}}} M_{S_{21},k}^{e^{h_1}} + \sum_{k=1}^{N_{S_{11},t}^{e^{h_2}}} M_{S_{11},k}^{e^{h_2}}.
\end{aligned} \tag{11}$$

Both terms are independent, because we assume only recovery times of one day and therefore no interaction between both hazard events. Therefore we calculate just the sum of the variances and again using the law of total variance:

$$\mathbf{Var}[V_t] = \mathbf{E}[N_{S_{21},t}^{e^{h_1}}\mathbf{Var}[M_{S_{21}}^{e^{h_1}}]] + \mathbf{Var}[N_{S_{21},t}^{e^{h_1}}\mathbf{E}[M_{S_{21}}^{e^{h_1}}]] + \mathbf{E}[N_{S_{11},t}^{e^{h_2}}\mathbf{Var}[M_{S_{11}}^{e^{h_2}}]] + \mathbf{Var}[N_{S_{11},t}^{e^{h_2}}\mathbf{E}[M_{S_{11}}^{e^{h_2}}]].$$

For the terms with e^{h_1} (so firm S_{21}) we obtain (analog as above):

$$\begin{aligned}
\mathbf{E}[N_{S_{21},t}^{e^{h_1}}\mathbf{Var}[M_{S_{21}}^{e^{h_1}}]] + \mathbf{Var}[N_{S_{21},t}^{e^{h_1}}\mathbf{E}[M_{S_{21}}^{e^{h_1}}]] &= \mathbf{Var}[M_{S_{21}}^{e^{h_1}}]\,\mathbf{E}[N_{S_{21},t}^{e^{h_1}}] + \mathbf{E}[M_{S_{21}}^{e^{h_1}}]^2\,\mathbf{Var}[N_{S_{21},t}^{e^{h_1}}] \\
&= \lambda_{S_{21}}^{e^{h_1}} t\,\mathbf{E}[(M_{S_{21}}^{e^{h_1}})^2].
\end{aligned}$$

So, all in all we obtain the following expression:

$$\mathbf{Var}[V_t] = \lambda^{e^{h_1}} t\, \mathbf{E}[(M^{e^{h_1}})^2] + \lambda^{e^{h_2}} t\, \mathbf{E}[(M^{e^{h_2}})^2].$$

If we assume that the intensities are equal across hazard events $e^h = e^{h_1} = e^{h_2}$ we can write

$$\mathbf{Var}[V_t] = \lambda^{e^h} t\, \xi^2_{S_{11}F_{01}} \, (\mathbf{E}[(IC^{e^{h_1}}_{S_{21}}\, \xi_{S_{21}S_{11}})^2] + \mathbf{E}[(IC^{e^{h_2}}_{S_{11}})^2]).$$

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Bottleneck identification in supply chain networks

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A version of this paper is published in the *International Journal of Production Research*[*]

This paper was presented at:

- 22$^{\text{nd}}$ International Conference of the Production and Operations Management Society (April 2011)
- 2$^{\text{nd}}$ Annual Conference of the European Decision Science Institute (June 2011)
- the research seminar at the Hong Kong City University (July 2011)

Abstract

In supply chain risk management, it is essential to identify firms that induce high losses due to supply chain disruptions in a focal firm or the supply chain network as a whole (bottlenecks). In this paper, we describe supply chain networks as complex systems of firms and their suppliers. We revisit some established network measures and compare their predictions with a new methodology for detecting bottlenecks. In this bottom-up approach, production disruptions on the firm level are modeled with stochastic point processes, and a mechanism for the propagation of losses through the network is defined. The individual firms' emerging loss contributions to the total losses of the focal firm provide, then, an alternative risk-adjusted measure. Our methodology and findings enable more informed and transparent decisions to be made for optimal supply chain network design.

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[*]K. Mizgier, M. P. Jüttner, and S. M. Wagner (2013), 'Bottleneck identification in supply chain networks,' International Journal of Production Research (IJPR), 51 (5), forthcoming.

1 Introduction

Supply chain networks (SCNs) are becoming larger and more densely interconnected, which increases the inherent complexity and uncertainty of production. The pressure of increasing competition and the possibilities of globalized markets have driven firms to outsource manufacturing globally to reduce inventories or economize the supply base. Although production processes are becoming more efficient (for example, through technological advances, see Brynjolfsson and Hitt 2000), the complexity of these networks makes it difficult to predict losses due to production breakdowns in the supply chain. On the other hand, many of the lean initiatives undertaken by the major car producers in the last two decades have striven to simplify supply network structures and reduce both the number of tiers and the number of entities at each tier. Indeed, much of the evident risk involves reduced diversification, albeit with a simplified structure. The correct assessment of the firm's risk exposure embedded in the actual network design is still a highly debated issue. Due to insufficient knowledge regarding the impact or correlation of hazard events and the dispersion of losses through the network, it is unclear whether certain network structures are more resilient or more susceptible to supply chain disruptions in single or multiple nodes in the SCN. In particular, it is essential that focal firms identify their high-risk suppliers. Supply chain risk managers are then able to reconfigure the network structure or improve resilience by introducing additional inventories to mitigate or prevent contagious effects.

This paper compares a set of measures for the identification of bottlenecks in SCNs. First, we revisit some established measures from social network theory, e.g., degree centrality or betweenness, and analyze them in the SCN context. Second, we introduce a new methodology for an efficient and accurate detection of firms in a SCN that potentially generate high losses for a focal firm in the case of a disruption. We use a simple bottom-up approach, in which supply chain disruptions are modeled on the firm level with stochastic point processes. A mechanism for the loss propagation through the network is defined. We determine via Monte Carlo (MC) simulation the aggregate loss distribution for the focal firm. The loss contribution of the individual firms and hazard events to total losses for the focal firm provide, then, a risk-adjusted measure. These measures aim to condense the complex informational content of a given network topology. However, it is crucial to our interpretation to consider the nature of the network connections. In SCNs, these connections occur on different interaction levels, including information channels, the flow of physical goods or, in our case, the loss dispersion induced by supply chain disruptions. We interpret and compare the results of these measures in the context of loss dispersion. Our findings support the need for an accurate methodology to identify firms in the SCN that greatly impact the losses of the focal firm.

The paper is organized as follows: Section 2 discusses the existing literature. The SCN under consideration is introduced in Section 3. In Section 4, we revisit centrality measures from network theory and discuss their applicability in the supply chain risk management context. We present our approach in Section 5. We discuss the results of both approaches in Section 6 and conclude in Section 7.

2 Literature review

Network theory has been widely applied in many research areas, spanning fields from the natural sciences (Dorogovtsev and Mendes 2003) to finance (Boss, Elsinger, Summer, and Thurner 2004), banking (Mistrulli 2011), economics (Allen and Gale 2000) and the social sciences (Granovetter 2005). The network paradigm developed in the aforementioned areas is fairly new to supply chain management (SCM). Nevertheless, we have observed a rapid growth in interest and applications in this domain. One of the initial studies of supply chains as complex systems was conducted by Macal (2003). Pathak, Day, Nair, Sawaya, and Kristal (2007) propose the Complex Adaptive System (CAS) perspective to study the interrelations that are often inherent in supply chain networks. Mizgier, Wagner, and Holyst (2012) develop an agent-based model to examine the defaults of companies in a supply chain network. They show how the dynamics of the relations among the supply chain members affect the system's performance. Yang and Yang (2010) study the role of postponement in supply chain risk management from a complexity perspective. Building on the normal accident theory, they conclude that in some circumstances the introduction of postponement may add to the complexity of a system and, thus, make the system inherently infeasible. Kumar, Tiwari, and Babiceanu (2010) analyze a mathematical model for supply chain network design under uncertainty. Considering the problem's complexity, they apply various computational techniques to offer potential solutions to robust supply chain design.

Several measures for bottleneck identification are proposed in the literature. Craighead, Blackhurst, Rungtusanatham, and Handfield (2007) derive six propositions relating the severity of supply chain disruptions to supply chain characteristics, such as density, complexity and node criticality. Their underlying theory involves identifying the most important nodes based on the measurement of information and the material flows between them. In this paper, we will concentrate on some basic definitions of node importance. Degree centrality and betweenness centrality are discussed by Freeman (1977). Opsahl, Agneessens, and Skvoretz (2010) propose modified algorithms and definitions, including the weighted connections. The use of these measures has many applications in social and natural sciences, such as scientific collaboration networks (Newman 2001) or biological metabolic networks (Ravasz, Somera, Mongru, Oltvai, and Barabási 2002). The algorithms used for the calculation of the centrality measures can be found in Brandes (2008). A thorough overview of the social network approach to SCM is provided by Borgatti and Li (2009). They state, that network theory has the potential to enrich SCM research with new tools and that network theory supports the creation of a coherent management science perspective. Choi and Kim (2008) and Choi and Wu (2009) use examples to show how to manage suppliers based on their embeddedness in the network and the strategic formation of triads. Such a view of the supplier base encourages buying firms to develop more realistic policies and strategies when managing their suppliers. Diabat, Govindan, and Panikar (2011) apply graph theory to illustrate the conceptual relationships between the risks in a food supply chain. An empirical investigation of a supply chain network has been carried out by Kim, Choi, Yan, and Dooley (2011). Their framework relates key social network analysis metrics to supply chain networks and proposes SCM-specific implications. They also provide a comprehensive literature review for readers interested in topics related to social networks.

3 Supply chain network structure

A SCN $\mathcal{V} = \mathcal{F} \cup \mathcal{S} = \{F_{01}, F_{02}, \ldots\} \cup \{S_{11}, S_{12}, \ldots, S_{21}, \ldots\}$ consists of $|\mathcal{F} \cup \mathcal{S}| = N$ agents divided into focal firms $\mathcal{F}$ and suppliers $\mathcal{S}$ on different tiers denoted by S_{kl} where k indicates the tier and l the number of the supplier on the specific tier. In the following we only consider one focal firm F_{01}. The relationships between the firms are described by a *directed graph* associated with the adjacency $\boldsymbol{\Xi} = (\xi_{ij})_{i,j=1,\ldots,N}$. The entry ξ_{ij} represents the purchasing volume sourced by firm j from firm i, expressed as the percentage of the total order per time unit. It can also be interpreted as the exposure of j to i, because if supplier i suffers a production disruption the ordered products cannot be delivered and the buying firm j will be negatively affected. Note that the first row corresponds to the volume the focal firm purchases from its suppliers. The matrix collects the direct business dependencies reporting the maximum exposure of a firm (business volume) if a disruption in one of the neighboring firms occurs. The impact of disruptions on stages farther in the network is not considered. Additionally, we introduce the matrix $A = (a_{ij})_{i,j=1,\ldots,N}$ where the entry a_{ij} is one if there is an edge from a node i to a node j, otherwise zero. The network structure is assumed to be static.

We use the following stylized example throughout the rest of the paper. We study a supply chain network with six agents: one focal firm F_{01} with three suppliers in the first stage S_{11}, S_{12}, S_{13} and two suppliers' suppliers S_{21}, S_{22} (second stage). The network structure is depicted in Figure 1. The matrix $\boldsymbol{\Xi}$ is given by

$$\boldsymbol{\Xi} = \begin{pmatrix} 0 & 0 & 1 & 0.8 & 0.6 & 0 \\ 0 & 0 & 0 & 0.2 & 0.4 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.7 \\ 0 & 0 & 0 & 0 & 0 & 0.2 \\ 0 & 0 & 0 & 0 & 0 & 0.1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} . \tag{1}$$

First, in the last row of $\boldsymbol{\Xi}$ we see that the focal firm F_{01} does not sell any products to agents within the network. For our purpose to study the downstream risk for this focal firm all connections to possible clients to F_{01} are naturally not considered. F_{01} herself receives all products or necessary components from all three direct suppliers, where for instance $\xi_{S_{11}F_{01}} = 0.7$ or $\xi_{S_{13}F_{01}} = 0.1$ (fifth row). A disruption in the production process of firm S_{11} (S_{13}) can induce a 70% (10%) reduction of delivery volume of F_{01}. On the other hand, for S_{11} all necessary components are sourced from supplier S_{21}, for S_{12} components are sourced 80%, 20% from supplier S_{21}, S_{22} respectively. We assume total disruptions (indirect costs of 100%). This stylized example has been discussed in

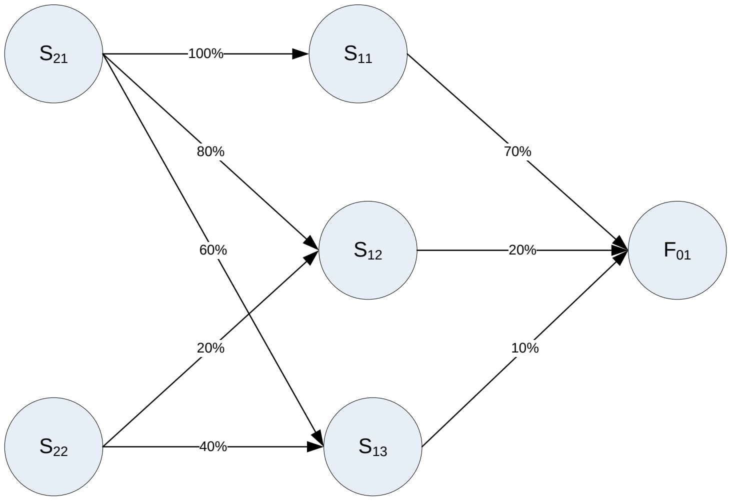

Figure 1: A sample supply chain network with with two stages of suppliers.

several meetings with our industry partners to ensure the feasibility of our approach.

4 Network theory-based measures for bottleneck identification

In graph theory and related applications measures exist to determine the rank or centrality of nodes according to their position in the network (see, for example, Freeman (1977), Brandes (2008), Opsahl, Agneessens, and Skvoretz (2010)). A thorough overview of centrality metrics and applications in SCM can be found in Kim, Choi, Yan, and Dooley (2011). Though these measures help identify the relative importance of nodes in a network, the context of the application is important. We apply the centrality measures to our simple example and describe some of the shortcomings when using the respective measure for risk management purposes. For the calculation and visualization of these measures, we use Visone, a freeware software developed at the University of Konstanz.[1]

For the SCN $(\mathcal{V}, A)$ one of the simplest measures is the *degree centrality* $C_D(v)$ (outdegree) for vertex $v \in \mathcal{V}$. $\mathcal{V}$ (with $|\mathcal{V}| = N$) is the set of nodes representing the firms and A describes the edges representing the business weightings between the firms. $C_D(v)$ is defined as follows:

$$C_D(v) = \frac{deg(v)}{N-1}, \tag{2}$$

where $deg(v)$ is the number of links node v directs to others (downstream), i.e., these firms are directly affected by a disruption of the production process in v. Several shortcomings exist: first, the network topology is only partially anticipated because only direct links are relevant; second, the weightings of the edges are not considered; third, the risk of a disruption in each node is not included. The results are depicted in Figure 2. Not surprisingly, supplier S_{21} is the most important node for our sample SCN, due to its high connectivity with other suppliers. Following Freeman (1977) the *betweenness centrality* counts the fraction of shortest paths between each

[1]For more information see `www.visone.info`.

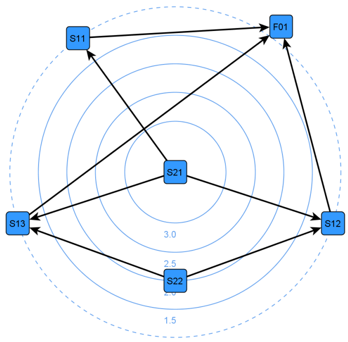

Figure 2: The relative importance of the suppliers, based on the outdegree.

pair of vertices that are passing through a given node $v \in \mathcal{V}$, in the following formula:

$$C_b(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}, \tag{3}$$

where σ_{st} is the number of shortest paths from s to t, and $\sigma_{st}(v)$ is the number of shortest paths from s to t that pass through a vertex v. The result is standardized by dividing it

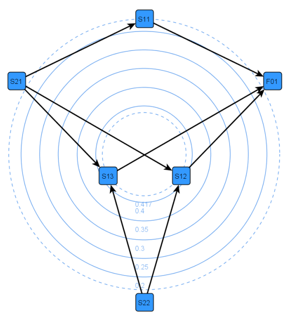

Figure 3: The relative importance of the suppliers, based on the betweenness centrality measure.

through the term $(N-1)(N-2)$, which corresponds to the maximum number of edges in a directed graph. The theory behind this concept is that nodes between others are central because they can influence the flow of information. In the case using weighted links, Brandes (2001) proposes to invert the weights while computing betweenness centrality. He also introduces several computationally efficient algorithms. In the case of the propagation of losses in an SCN, this measure appears misleading because firms on the outermost stage of the SCN are not identified as risk sources. The information flow, in contrast to loss dispersion, should be sustained, and, therefore, disruptions in the nodes present between other nodes are central. For the area of loss propagation in SCNs, these disruptions can have a positive effect because the contagious effects are absorbed. On the other hand, if losses are not absorbed, these nodes in the network appear to be central the loss propagation. In Figure 3, we see that the group of suppliers S_{12}, S_{13} is marked with the highest values of centrality. For a supply chain manager, this result indicates that this group of suppliers is highly clustered, and is, therefore, vulnerable to collective disruptions. The next measure, which can be used to support identification of the

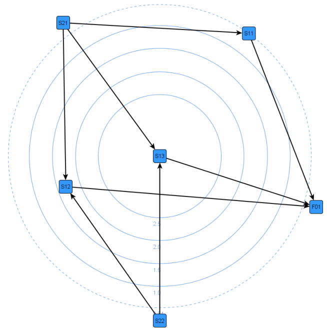

Figure 4: The relative importance of the suppliers, based on the weighted betweenness centrality measure.

most critical suppliers is called radiality (Valente and Foreman (1998)). Radiality is the degree of supplier's connectivity when reaching out into the network. It is defined as follows:

$$R(k) = \frac{\sum_{j \neq k} RD_{jk}}{N-1}, \tag{4}$$

where RD_{jk} is the reverse distance computed from the geodesic between suppliers j and k, measured on outdegree ties and N is the network size. High radiality means that fewer steps, on average, are necessary for that supplier to deliver goods to everyone else in the network through her distribution channels (outdegree ties). In terms of supply chain disruptions, a supplier with high radiality would affect more firms in the network if a disruption occurred. The results of analysis based on node radiality are depicted in Figure 5.

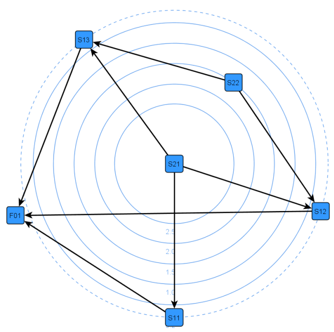

Figure 5: The relative importance of the suppliers, based on the radiality measure.

5 Alternative method for bottleneck identification

In this section, we first model the frequency and severity of disruptions on each firm's production process. In the second subsection, we define the loss propagation through the network. In the last subsection, we implement the model for the examplary SCN, generate via MC simulation a loss distribution for the focal firm and study the impact (loss contribution) of single nodes to the total average loss of the focal firm. In performing these measures, we are able to identify potential bottlenecks in the focal firm's supplier structure, i.e., the suppliers with the highest loss contributions.

5.1 Disruption risk: frequency and severity

We model disruption risks (frequency and severity) on the firm level using renewal-reward processes. We first identify potentially disruptive supply chain events for each node in the network. The finite set $\mathcal{E} = \{e_1, \ldots, e_E\}$ collects all possible events of all nodes in the network; $\mathcal{E}_j$ then denotes the set of possible hazard events for firm j. We can distinguish two types of disruptions: firm-specific and systematic hazard events. The term systematic is only used for the simultaneous dependence of different firms in the network on the same hazard event and not the simultaneous impact due to interfirm links (contagion). The variable $(N^{e_i}_{j,t})_{t>0} \in \mathbb{N}_0$ is the random number of disruption event e_i that occur during the period $[0, t]$ in node j. The probability function is denoted is by $p^j_{e_i,t}(k) = \mathbf{P}[N^{e_i}_{j,t} = k]$. The cumulative density function (cdf) for the loss frequency is then obtained by

$$\mathbf{P}[N^{e_i}_{j,t} \leq n] = \sum_{k=0}^{n} p^j_{e_i,t}(k). \tag{5}$$

It is necessary to determine the theoretical distribution and parameters that best fit to the empirical distribution of documented historical occurrences. The disruption frequency is often modeled by a Poisson or negative binomial distribution. In contrast, the impact of a disruption differs across firms because firms have different approaches to organization and business continuity management. The required time for firm j to resolve the disruption due to event $e_i \in \mathcal{E}_j$ is described by the sequence of independent and identically distributed (iid.) and positive random variables (r.v.) $(R^{e_i}_{j,n})_{n\in\mathbb{N}}$. The production losses for connected nodes are denoted by $(IC^{e_i}_{j,n})_{n\in\mathbb{N}}$. These indirect costs represent reductions in production in percentage terms and per time unit. After a disruption occurs, the firm requires a random amount of time to resume the production process. As soon as production restarts, it is exposed to new disruptions. The entire time structure for a hazard event e_i is depicted in Figure 6. In the simulations in Section 5.3, we will assume that production times are exponentially distributed (Poisson process) and are independent across hazard events. According to this assumption, it is possible to aggregate these processes. We also impose the assumption that recovery times are non-stochastic and identical across hazard events, i.e., $R^{e_i} = r$ for $i = 1, \ldots E$.

The total indirect costs in terms of an exposure to hazard event e_i, with respect to direct neighboring firms in the network up to time t are given by

$$TIC^{e_i}(t) := \sum_{\{j\in\mathcal{S}\}|e_i\in\mathcal{E}_j\}} \left(\sum_{k=1}^{N^{e_i}_{j,t}} IC^{e_i}_{j,k}\, R^{e_i}_{j,k} \Big(\sum_{l>j} \xi_{jl} \Big) \right). \tag{6}$$

In equation (6), all firms with an exposure regarding hazard event e_i are collected. The result is given in relative terms, i.e., the entries of $\boldsymbol{\Xi}$ are given as percentages of purchasing volume.

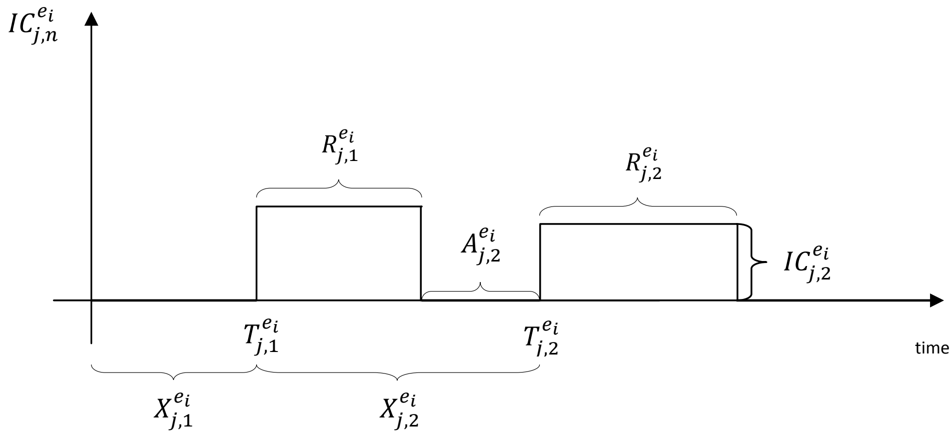

Figure 6: Basic disruption time structure of event e_i with production reduction $IC_{j,n}^{e_i}$, recovery time $R_{j,n}^{e_i}$, interruption time $T_{j,n}^{e_i}$, active time $A_{j,n}^{e_i}$ and interarrival time $X_{j,n}^{e_i}$.

5.2 Correlated business interruptions - dispersion

We have previously described the effects on the hazard event- and firm-specific levels. The complete hazard model for one firm j is consequently given by aggregating the events within the set $\mathcal{E}_j$. The correlation across the nodes in the network is established by two channels: first, the intersection of firm-specific hazard event sets is not necessarily empty, i.e., $\mathcal{E}_j \cap \mathcal{E}_i \neq \{\}$ (systematic risk) and second, the network naturally produces a dependency structure across the firms. Therefore, idiosyncratic disruptions also propagate through the network and affect other firms (contagion).

For the second aspect of correlated losses we must describe how disruptions that occur in the farther stages propagate and affect other firms in the network. In this way, they also affect the focal firm through the existing connections. As mentioned previously, $\mathbf{\Xi}$ describes the business weightings between the firms. The $n-$th power of the matrix $\mathbf{\Xi}$ power of the matrix describes the impact on firms from respective suppliers on the n-th stage exclusively (without disruptions on intermediate stages). We assume that there is no inventory to absorb even part of the potential supplier disruptions. This implies that losses are transferred without any friction. The simultaneous occurrence of disruption events is also important: we anticipate the effects of each disruption event and the associated losses separately, but we must impose the constraint that aggregated losses will not exceed the indirect losses of direct neighbors, i.e., we follow the complete path of each disruption through the network. Hence, the propagation of losses from one stage to the next stage is restricted to the maximum loss of the 'nearer' (or next) stage.

5.3 Simulation setting and loss contribution

The SCN is given by the adjacency matrix in equation (1). The time horizon is set to 180 days, and we perform 1000 MC iterations. First, we assume that two idiosyncratic hazard events exist for each firm. Therefore, we simulate two independent Poisson processes with corresponding intensities on each node. The intensities can be found in the first column of Table 1. Later, we also incorporate an event e^h (third column) that can have an impact on more firms in the network. In our case, e^h has an impact on node S_{13} and S_{21}, i.e., here we simulate one Poisson process with intensity 0.001. Therefore, the time structure $(T^{e^h}_{j,m})_m$ of this event is the same for both firms. We keep the 'initial' average recovery time $r^{e_i}_j$ of three days for hazard events 1 and 2 (HE1 and HE2) and 14 days for hazard events of type 3 (HE3). We calculate the relative

Hazard Event 1	**Hazard Event 2**	**Hazard Event 3**
$\lambda^{e^1_{S_{11}}} = 0.01$	$\lambda^{e^2_{S_{21}}} = 0.01$	$\lambda^{e^h_{S_{21}}} = 0.001$
$\lambda^{e^1_{S_{12}}} = 0.015$	$\lambda^{e^2_{S_{22}}} = 0.005$	$\lambda^{e^h_{S_{22}}} = 0.001$
$\lambda^{e^1_{S_{13}}} = 0.01$	$\lambda^{e^2_{S_{11}}} = 0.01$	$\lambda^{e^h_{S_{11}}} = 0.001$
$\lambda^{e^1_{S_{21}}} = 0.02$	$\lambda^{e^2_{S_{12}}} = 0.05$	$\lambda^{e^h_{S_{12}}} = 0.001$
$\lambda^{e^1_{S_{22}}} = 0.01$	$\lambda^{e^2_{S_{13}}} = 0.01$	$\lambda^{e^h_{S_{13}}} = 0.001$

Table 1: Intensities of hazard events.

contributions to the total losses of the focal firm by each node. We identify their impact on the focal firm in two ways. First, we simulate disruptions for only the single nodes and assume that losses propagate through the network unhindered (not mitigated or amplified), i.e., all other firms in the SCN are operating without disruption in their own production facilities. An efficient computation of these losses is made possible by using the squared business weighting matrix. Second, we simulate the actual hazard events in all the nodes and separate the contributions from the different nodes from the total losses of the focal firm. It is possible that disruptions from second stage suppliers do not affect the focal firm because simultaneous disruptions on the first stage prevent the loss propagation. This computation enables us to evaluate the each supplier's contribution to the risk exposure and its impact on the focal firm, which is not isolated but embedded in the risk environment of the whole SCN. In the following figures, the blue (green) bars depict the first 'isolated' (second 'embedded') case.

We start by simulating only the idiosyncratic events HE1 and HE2, thus neglecting correlation effects induced by HE3. In Figure 7 we summarize the mean percentage value of losses coming from a given supplier as the measure of nodes' importance. We can see that independent of the way we map losses to separate nodes, the supplier S_{21} accounts for approximately 36% of the losses, followed by nodes S_{11} (28%) and S_{12} (27%). If we look more closely at the values of suppliers' hazard event intensities, we observe that the network structure is the crucial factor in bottleneck identification. Although the intensities of the hazard events are comparable, the business volumes and the interconnectedness of a given node play the most important roles. Our approach clearly shows that supplier S_{21} has the highest relevance in terms of generated losses and its impact on the focal firm's risk exposure. Next, we add the systematic hazard event HE3 to analyze the influence of the correlated disruptions. As Figure 8 shows, the distribution of the blue bars representing the first case does not change much. This is obvious because the effect of HE3 is only observable when hazard events of different firms interact which is assumed not to occur in the isolated case. Instead, the difference in the distributions of the green bars

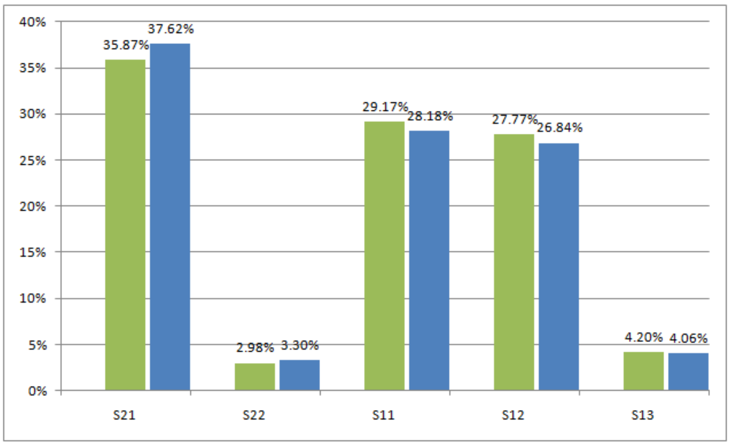

Figure 7: The relative importance of the suppliers, based on the percentage loss contribution. Green bars: embedded, blue bars: isolated.

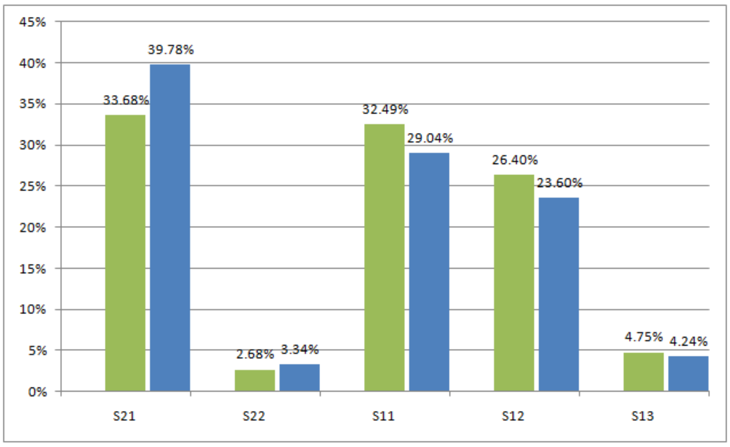

Figure 8: The relative importance of the suppliers, based on the percentage loss contribution with a correlated hazard event. Green bars: embedded, blue bars: isolated.

is very clear. Suppliers S_{21} and S_{11} are now nearly equal. It comes from the fact that the losses generated on the second stage are not propagated when disruptions occur on both stages simultaneously, which is always the case for HE3. In a third step, we demonstrate the impact

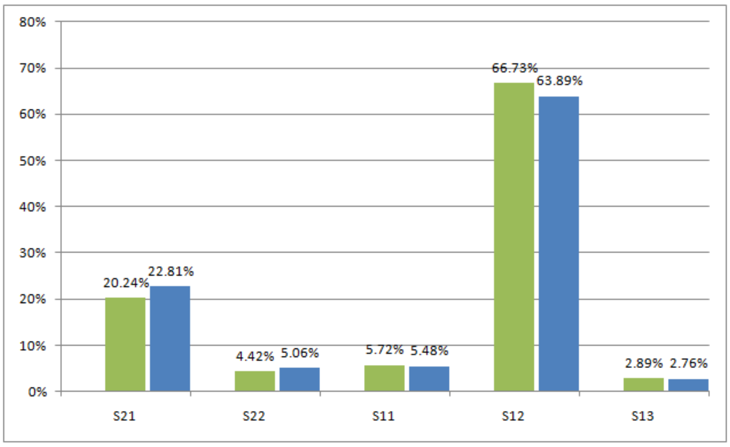

Figure 9: The relative importance of the suppliers, based on the percentage loss contribution (modified business weightings). Green bars: embedded, blue bars: isolated.

of a changed network structure. We can imagine that a focal firm influences the first stage of suppliers. The firm decides to switch purchasing volumes. In this setup, the network structure remains as it was, but purchasing volumes from suppliers S_{11}, S_{12} and S_{13} are adjusted to 20%, 70% and 10%, respectively. We present the results for HE1 and HE2 in Figure 9 and with the additional systematic hazard event in Figure 10. In both settings supplier's S_{12} loss

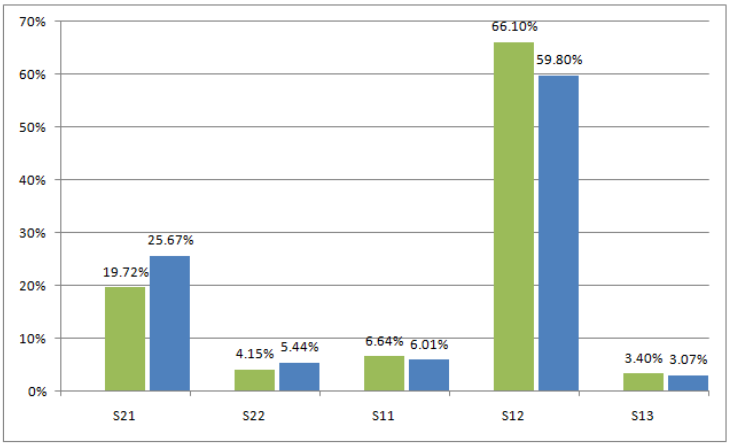

Figure 10: The relative importance of the suppliers, based on the percentage loss contribution with correlated hazard event (modified business weightings). Green bars: embedded, blue bars: isolated.

contribution surges and it becomes the only bottleneck with approximately 66%. The impact of an additional systematic hazard event is similar to the results of the previous analysis. The technique presented above can be applied to any given network structure, providing managers with a risk-based optimization support tool for decisions about the supply chain network design.

6 Comparison of results, discussion and implications

Table 2 summarizes the results of the introduced network theory-based measures from Section 4 (first four columns) and juxtaposes the outcome with the loss contributions (LCs) of our simulation approach (last two columns). The bold letters indicate the node in the SCN with the highest importance according the respective measure. We observe in our calculations that the results for bottlenecks in the SCN vary massively dependent on the centrality measure or risk structure. Node S_{21} is identified as the most important production facility using degree centrality or the first case (two independent hazard events) of our approach. Betweenness centrality predicts that the nodes on the first stage S_{12} and S_{13} are the prominent facilities in the SCN. For the management of SCNs this variety of results is not desirable. As pointed out before: the concrete context, interpretation and application is essential for using these measures and not being misled. Table 3 compares directly the results of 'isolated' and 'embedded' LCs when we incorporate an additional systematic hazard event. Adding the third hazard event to each node which represents a correlated disruption, changes the picture dramatically. Now, the impact in the embedded case of S_{21} and S_{11} are almost the same. Such a change in the risk structure does not change the results of the established measures.[2] The 'real' inherent SCN risk changed but

[2]One possibility to incorporate this feature one would have to adjust the weightings by the risk of hazard events.

Table 2: Comparison of bottleneck measures - benchmark case: $C_D(v)$ ($C_b(v)$) denotes the outdegree centrality (betweenness centrality) measure introduced in equation (2) ((3)). The bold letters indicate the node with the highest importance according the respective measure. Loss contribution (LC) is the loss for the focal firm F_{01} induced by node v relative to total losses.

Node v	$C_D(v)$	$C_b(v)$ (uniform)	$C_b(v)$ (weighted)	Radiality	Loss Contribution (LC) (isolated)	LC (embedded)
F_{01}	0	0.00	0.00	0.00	-	-
S_{11}	0.2	0.17	0.54	0.20	28.18%	29.17%
S_{12}	0.2	**0.42**	1.68	0.20	26.84%	27.77%
S_{13}	0.2	**0.42**	**2.83**	0.20	4.06%	4.20%
S_{21}	**0.6**	0.00	0.00	**2.80**	**37.62%**	**35.87%**
S_{22}	0.4	0.00	0.00	1.50	3.30%	2.98%

can only be identified by our advanced approach. Though the isolated case is superior in the computational simplicity it does not capture important aspects of the SCN risk. All in all, we think that simple measures can be helpful to obtain first indications regarding possible bottlenecks but these are definitely not conclusive. Table 4 presents the results of the modified SCN.

Table 3: Comparison of bottleneck measures - benchmark case with a systematic hazard event: The table presents the simulation results for the isolated (embedded) loss contribution (LC) if all nodes in the SCN are additionally exposed to a systematic hazard event HE3.

Node	LC (with HE3) (isolated)	LC (with HE3) (embeddeed)
F_{01}	-	-
S_{11}	29.04%	32.49%
S_{12}	23.60%	26.40%
S_{13}	4.24%	4.75%
S_{21}	**39.78%**	**33.68%**
S_{22}	3.34%	2.68%

With the exception of the weighted $C_b(v)$ all other network theory-based measures stay the same.

Table 4: Comparison of bottleneck measures - modified case without and with a systematic hazard event: This table shows the results for the modified SCN. The first two columns present the loss contribution when the nodes are dependent on firm-specific hazard events, the last two columns when an additional systematic hazard event is introduced.

Node	LC (isolated)	LC (embedded)	LC (with HE3) (isolated)	LC (with HE3) (embedded)
F_{01}	-	-	-	-
S_{11}	5.48%	5.72%	6.01%	6.64%
S_{12}	**63.89%**	**66.73%**	**59.80%**	**66.10%**
S_{13}	2.76%	2.89%	3.07%	3.40%
S_{21}	22.81%	20.24%	25.67%	19.72%
S_{22}	5.06%	4.42%	5.44%	4.15%

6.1 Discussion

From our results, we infer that each of the measures presented in this paper has both advantages and limitations, as summarised in Table 5. Simple network theory-based measures can be helpful in obtaining first indications regarding possible bottleneck identification, but these are definitely not conclusive. The more advanced concepts, such as radiality, are capable of including the entire network structure and following complete geodesic paths. Therefore, they contain more information about the global network design. They are also superior in terms of computational efficiency, as they do not require heavy numerical calculations. The main drawback of these methods is that they do not capture the dynamic properties of the supply chain disruptions and their propagation across the network. Here, our approach adds the most value, as it correctly captures the risk exposure to different hazards and includes the topological features of the SCN. Naturally, these improvements come at a cost. The performance of our method depends on the complexity of the network and the number of hazard events that must be included in the MC simulation. As we assume that waiting times between successive disruptions are exponentially distributed, the running time of our algorithm depends heavily on the quality and efficiency of the random number generators. Moreover, because the algorithms used to sort the graphs depend on the number of nodes and edges in the network, the time complexity of the algorithms will increase with the size of the network. After considering all these factors, we believe that combining our proposed method with the network measures will achieve accurate bottleneck identification to support supply chain risk management decisions. As computational power rises, the running time of our algorithms should be acceptable, even when applied to large-scale networks.

Table 5: Summary of measures for bottleneck identification.

Centrality measure	**Conceptual definition**	**Advantages**	**Disadvantages**
Out-degree centrality	The supplier is critical when it is connected to a large number of other suppliers	Easy to compute, can be used as a first measure of supplier's criticality	Measures only the impact on the directly connected firms
Betweenness centrality	The supplier is critical when it lies between many other suppliers	Includes the whole network structure	Raw material providers are not penalized even if critical due to their position in the network
Weighted betweenness centrality	The supplier is critical when it lies between many other suppliers	Includes the whole network structure and business weightings	Raw material providers are not penalized even if critical due to their position in the network
Radiality	The supplier is critical when its reachability to other suppliers is high	Includes the whole network structure	Raw material providers are penalized even if not critical due to their position in the network
Loss contribution approach	The supplier is critical when it generates the highest expected losses	Includes the whole network structure and all parameters of disruption risk	Computational complexity and high data requirements

6.2 Practical implications

Our study has several practical implications. First, the direct consequence of the presented comparison between the established network measures and our proposed loss contribution approach is the careful use of all measures. In particular, the data requirements for the established network measures are relatively low, and efficient algorithms already exist, which lends a great advantage to our new approach. Firms are tempted to apply these approximate and sometimes misleading indicators. Managers must always be aware of the respective purposes of each measure and operate with a set of different measures.

Second, the implementation of the appropriate approach necessitates the establishment of a detailed loss database. Therefore, guidelines for reporting and documenting losses from supply chain disruptions within the SCN (also across different firms) are required. The firm requires sufficient data about hazard events, respective frequencies, recovery times and corresponding losses to calibrate the model. The fulfilment of this requirement is certainly ambitious. The documentation and analysis of such a loss database is very helpful for sensibilising the work force regarding inherent risks in the SCN and optimising production and supply chain operations.

Third, our new method provides operations and supply chain managers with an efficient tool for the quantification of losses due to supply chain disruptions from single suppliers, both in isolation and when embedded in the network structure. They can both identify the most critical suppliers and estimate the potential impact of disruptions in absolute terms. These evaluations may have two consequences. On the one hand, managers may monitor these firms accurately to avoid the negative impacts caused by disruptions. They learn more about their business model, the risks of their suppliers' operations and locations and potentially have the ability to change some of the parameters. On the other hand, the quantification of losses based on the model input parameters allows managers to study the impact of reconfigured networks (as Figures 9 and 10 show). Our model can, therefore, be developed further, allowing for the automatisation and optimisation of risk-weighted allocations of purchasing volume. Using a stepwise comparison of purchasing volumes sourced from each supplier, supply chain managers can optimise the risk exposure of the entire SCN. A comparative statics analysis for all the input variables may also be helpful in identifying both important nodes and their risk exposure.

7 Conclusion

In this paper, we present a set of methods for identifying bottlenecks in an SCN. By incorporating the risk-specific features of the SCNs, we extend the set of measures proposed by Kim, Choi, Yan, and Dooley (2011). We demonstrate that some methods based on network theory may support the bottleneck identification process. However, they can also be misleading because they often focus only on a small part of the network or have been developed for a particular application, not for supply chain risk management. Therefore, we propose an alternative method of bottleneck identification that considers the features of modern supply chain networks. Moreover, we show that the reconfiguration of the supply chain network can offer substantial benefits regarding the reduction of the company's risk exposure in absolute terms. Using our bottleneck identification scheme, supply chain risk managers can easily discover which suppliers are strongly interconnected (critical) and pose the greatest threat to the focal firm. Our study is not without its limitations. We run simulations on a simplistic and stylised supply chain network structure. It would be desirable to test the measures on a real-world example and then to backtest the simulation results. However, we discussed the network structure with industry representatives to confirm the validity of the proposed model, and it is sufficiently complex for illustrative purposes. For a similar network setup, please refer to the study by Cossin and Schellhorn (2007). Nevertheless, we are aware of this limitation.

Our approach allows for further development of this model. Both the investigation of the network theory measures and the loss contribution method enable researchers to explore several research paths. It would be interesting from the network perspective to observe how the model behaves when the network under investigation increases in size and complexity. As noted by Brandes (2001), the fastest algorithms to compute the betweenness centrality and radiality measures require $O(N+A)$ space and $O(NA+N^2 logN)$ time, where N is the number of nodes and A the number of edges in the network. Therefore, the computational complexity and efficiency of the methods presented in this paper also present an interesting research avenue. We previously assumed in the simulation that the connections are deterministic and fixed. The incorporation of a more realistic, random graph may provide insight. Furthermore, the assumption of fixed values of hazard event intensities may be relaxed to incorporate seasonal effects. In stressed market phases, these intensities could increase, causing the picture to change fundamentally. The analysis of SCNs under stress – including strongly increased intensities – should be considered as an additional valuation tool. Another aspect that has potential for improvement is the integration of the risk structures of hazard events into existing network measures. One could modify the business weightings by the corresponding values of risk parameters and obtain the risk-adjusted network measures.

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